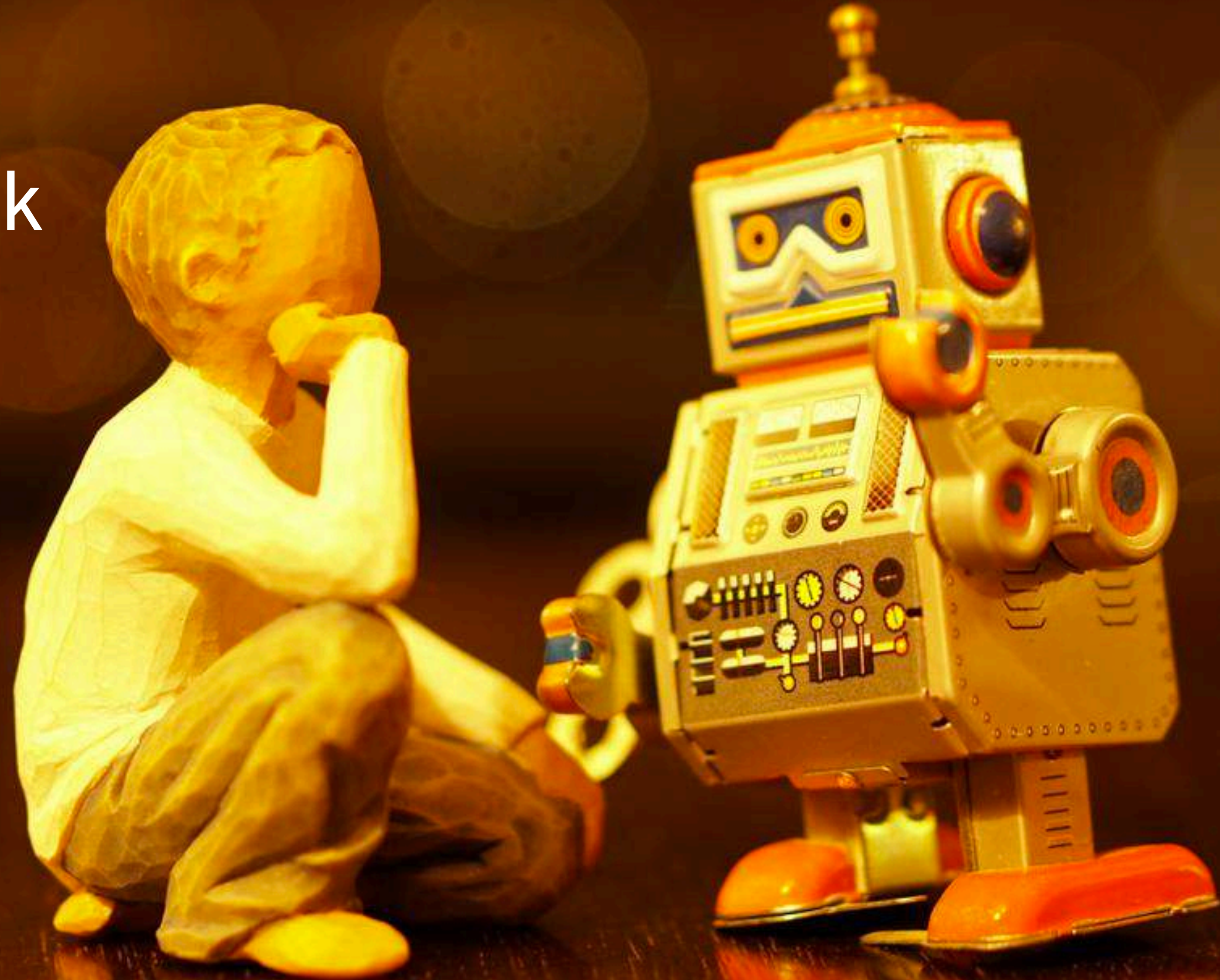


The complexity of skills and the future of work

Morgan R. Frank





 **Brad Wilson** 1 minute ago
We will soon have too many people.
👍 🗨️ REPLY

 **OTurbox** 1 minute ago
Who sheds a tear about these jobs?
👍 1 🗨️ REPLY

 **feeblezak** 3 minutes ago
Time for warehouse workers to unionise.
👍 1 🗨️ REPLY

 **BaikΦ** 3 minutes ago
bye bye humans in jobs...
👍 🗨️ REPLY

Source Subject

*Challenging due to missed detections



Everybody Dance Now (arXiv:1808.07371)

Skill biased technological change



Surgeons & Robotics



Engineers & Drones



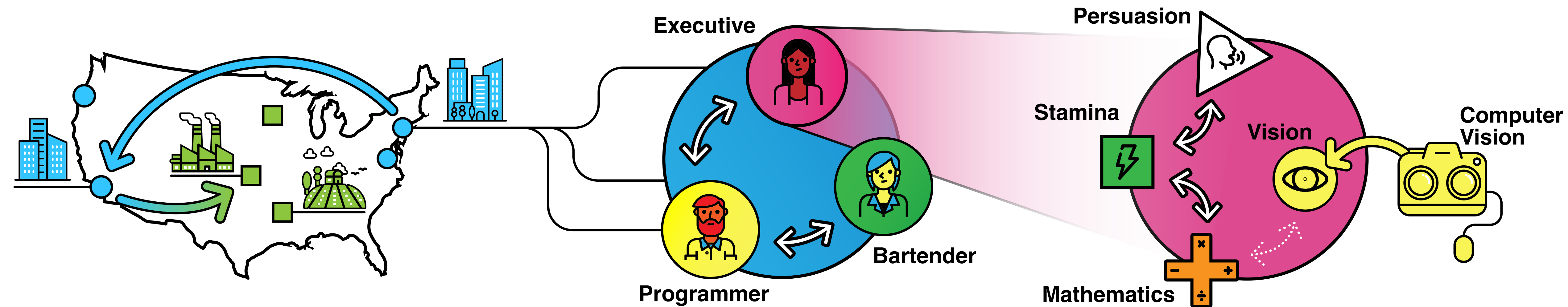
Bank Tellers & ATMs

A framework for skills, labor, and cities

Local Labor Markets

Occupations & Employment

Tasks & Skills



- differential impact of automation
- skill & wealth disparity
- spatial career mobility

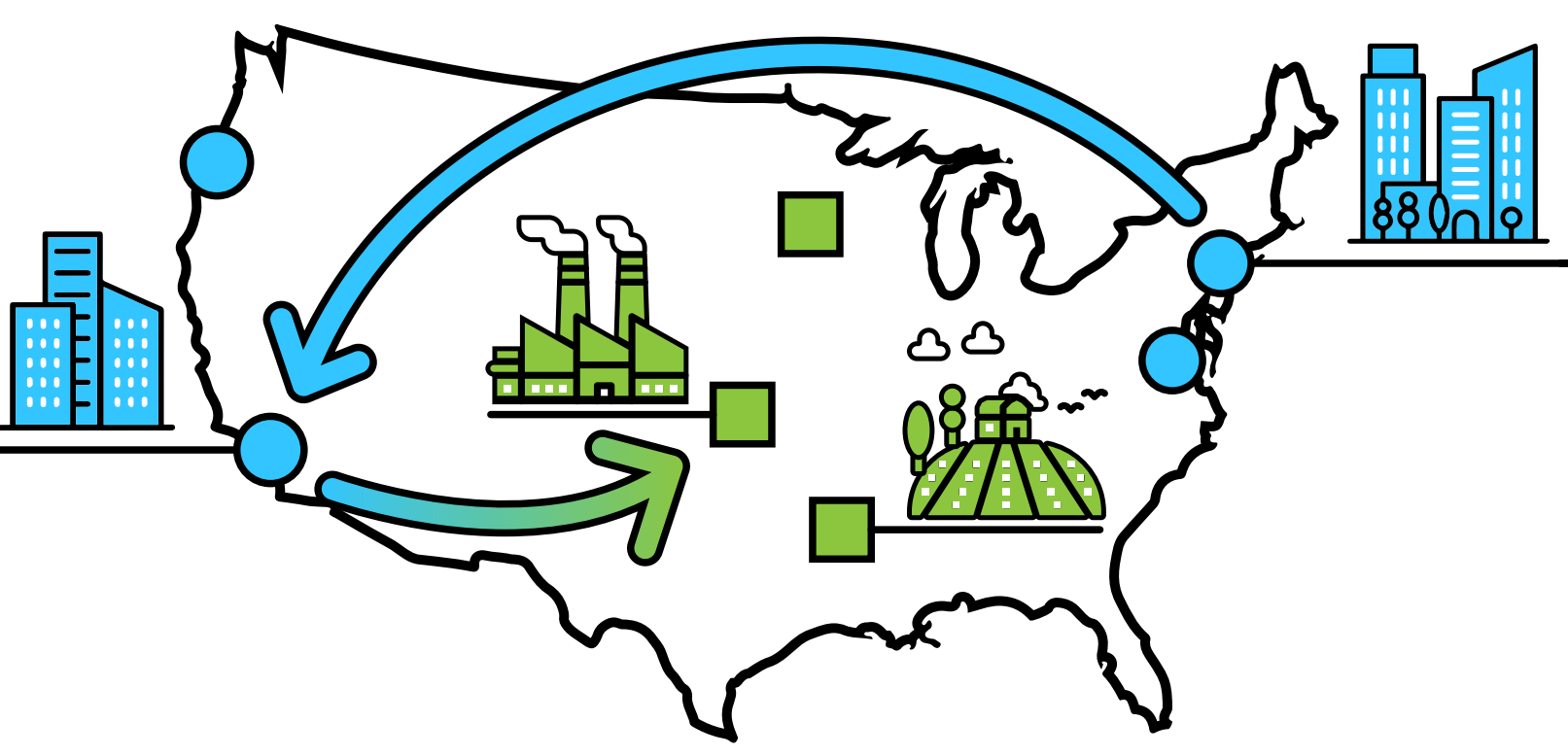
- career trajectories
- viable retraining
- job polarization

- interaction with technology
- skill complementarity
- education

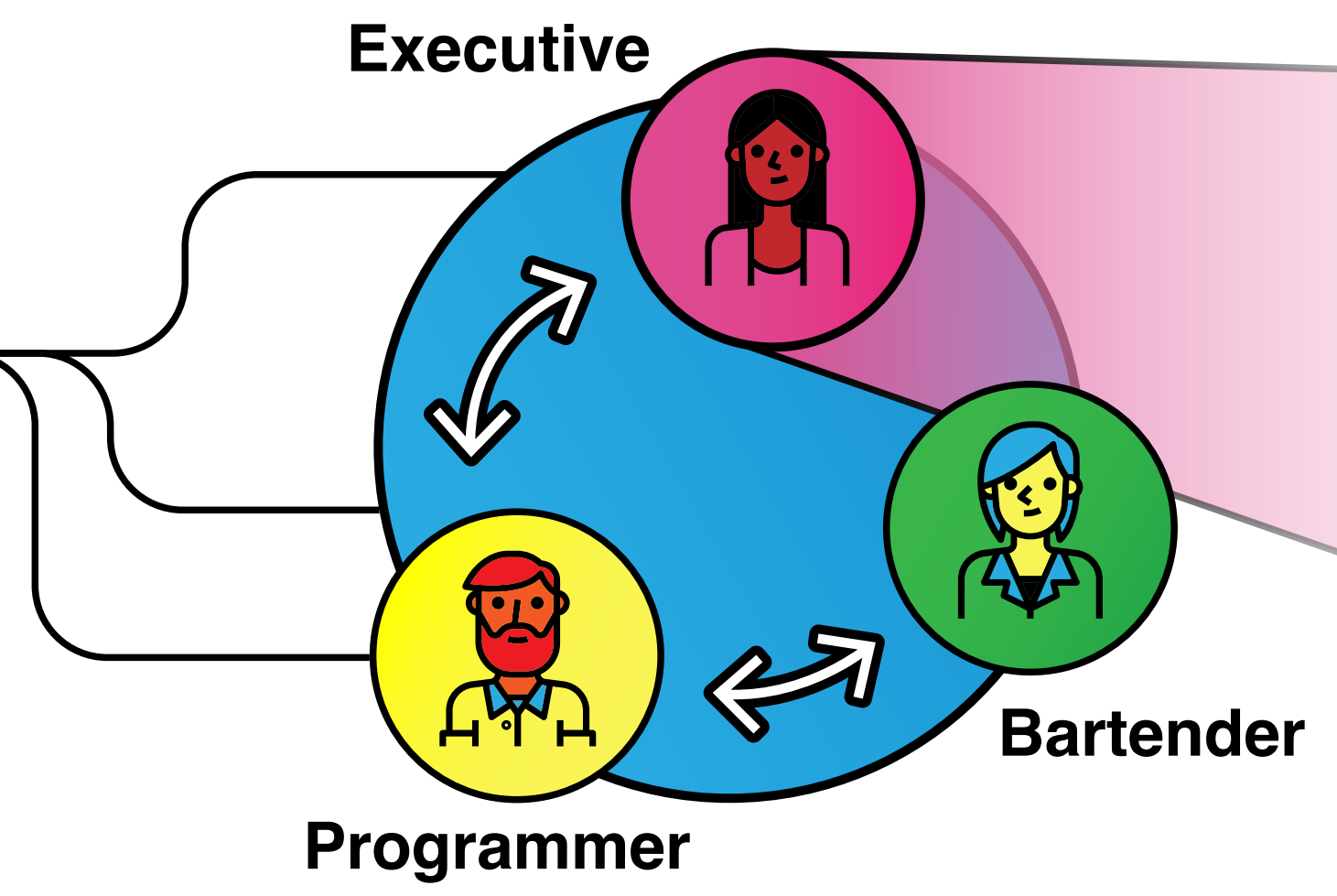
Frank et al., *PNAS* (2019)



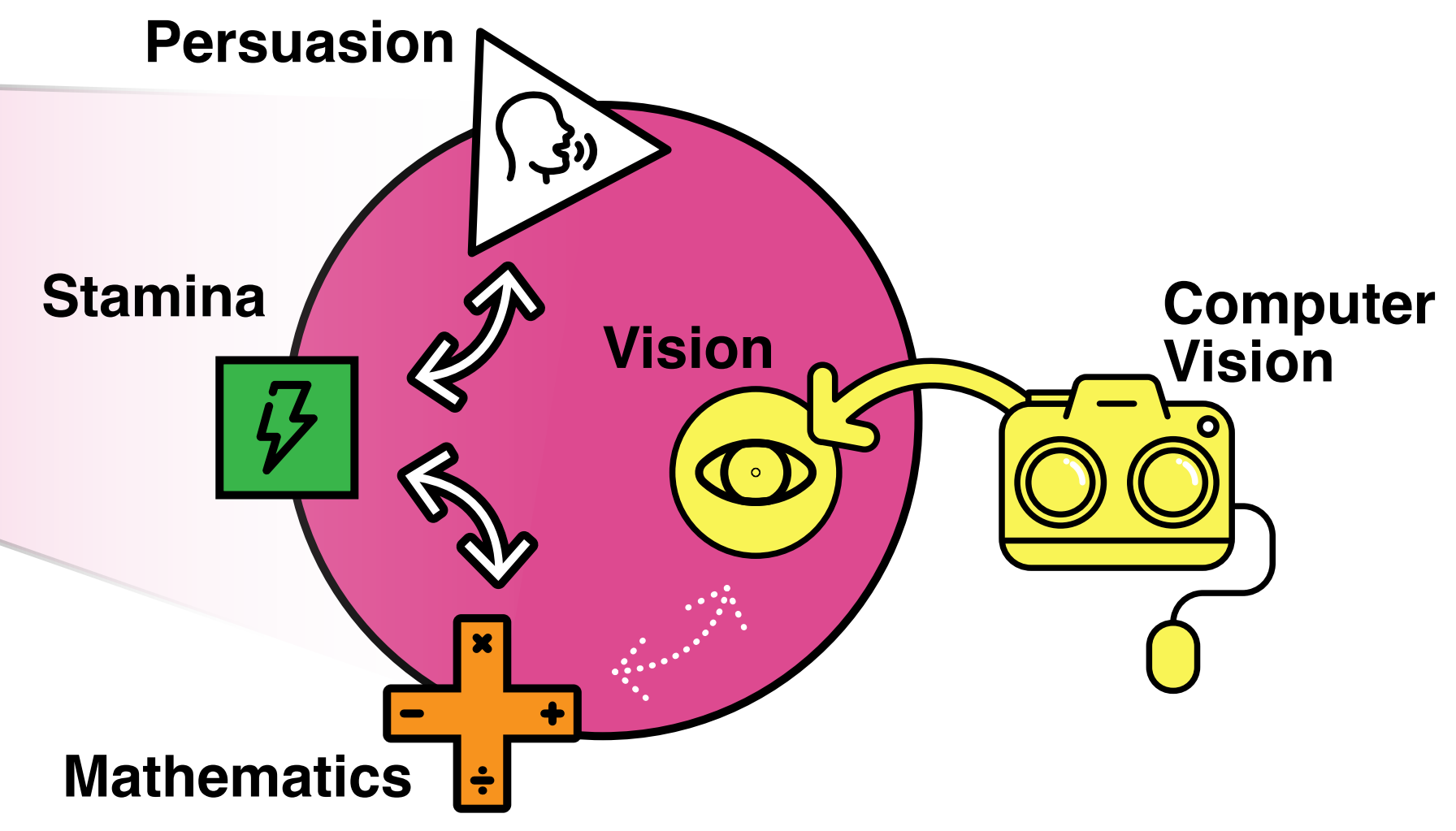
Local Labor Markets



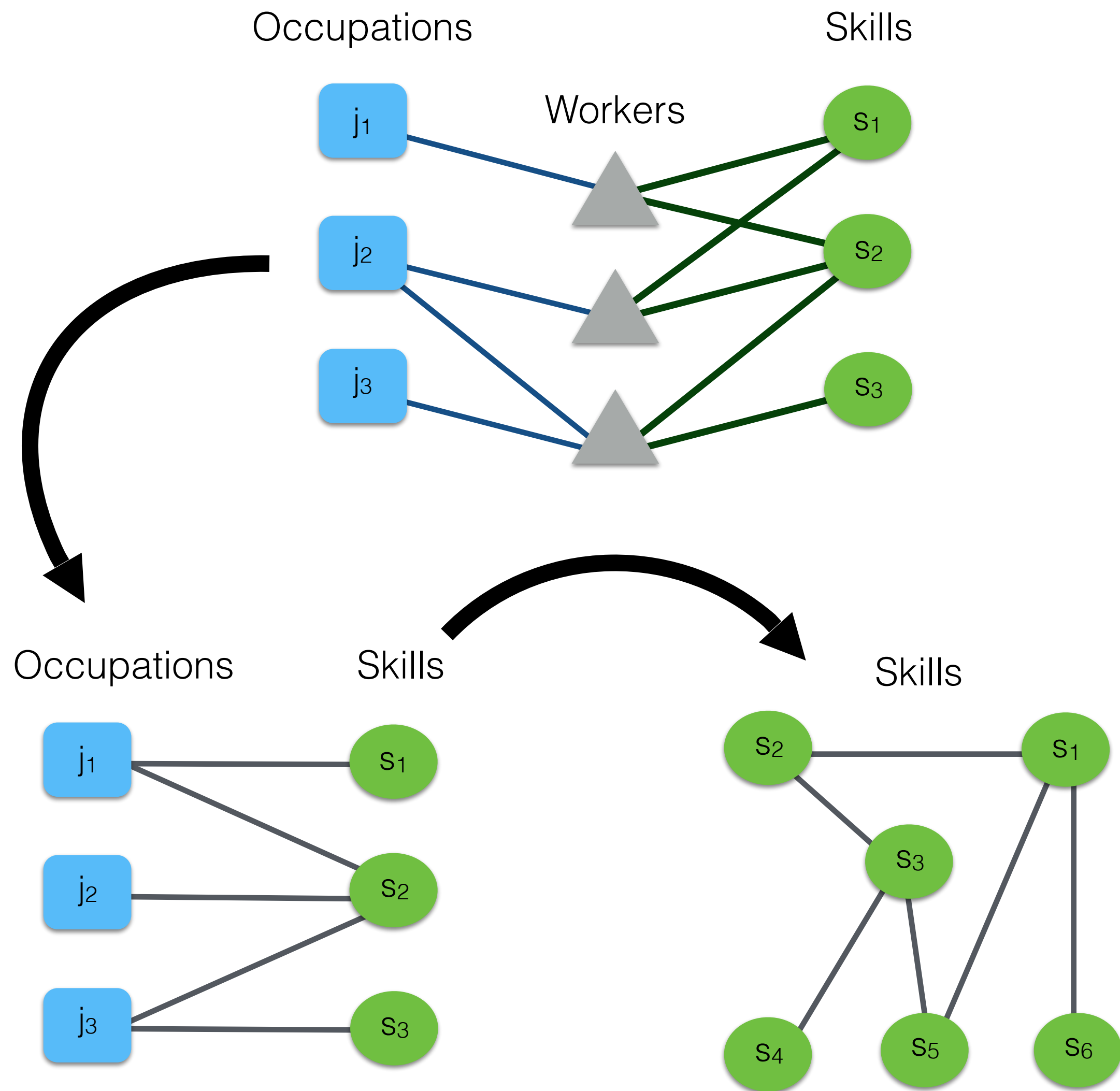
Occupations & Employment



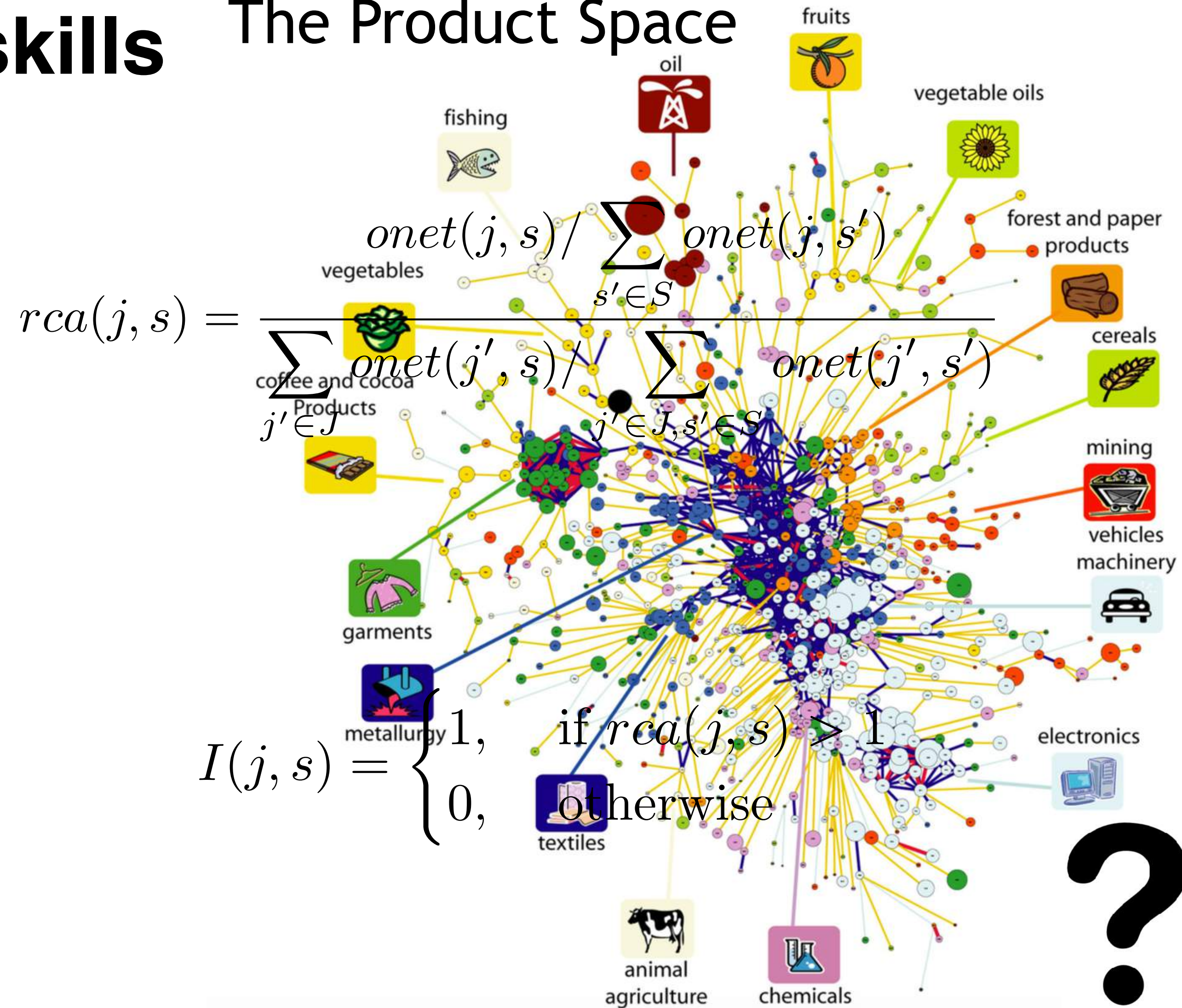
Tasks & Skills



The structure of workplace skills



The Product Space

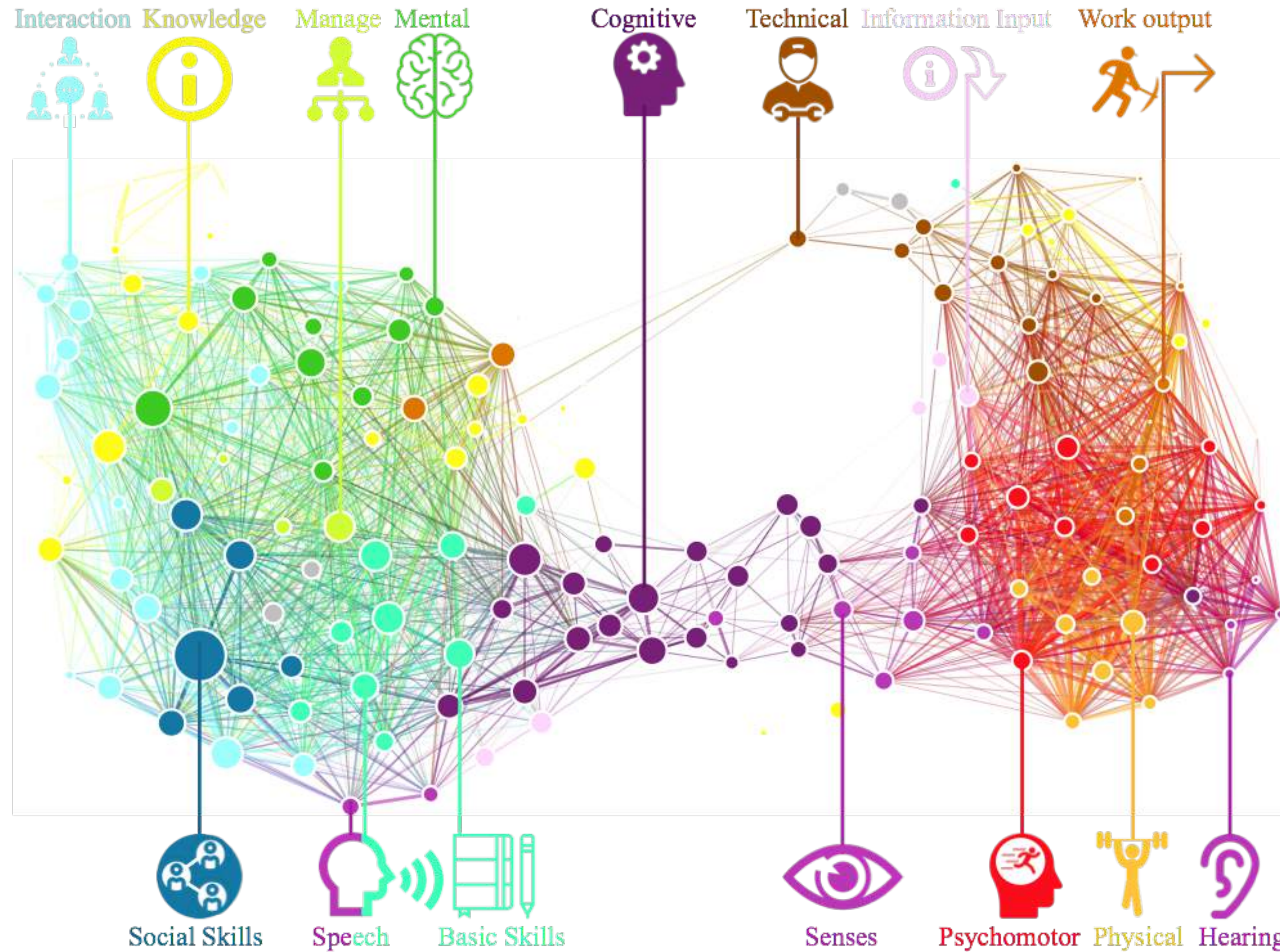


$$rca(j, s) = \frac{onet(j, s) / \sum_{s' \in S} onet(j, s')}{\sum_{j' \in J} onet(j', s) / \sum_{j' \in J, s' \in S} onet(j', s')}$$

$$I(j, s) = \begin{cases} 1, & \text{if } rca(j, s) > 1 \\ 0, & \text{otherwise} \end{cases}$$

Science Advances (2018)

Unpacking the polarization of workplace skills



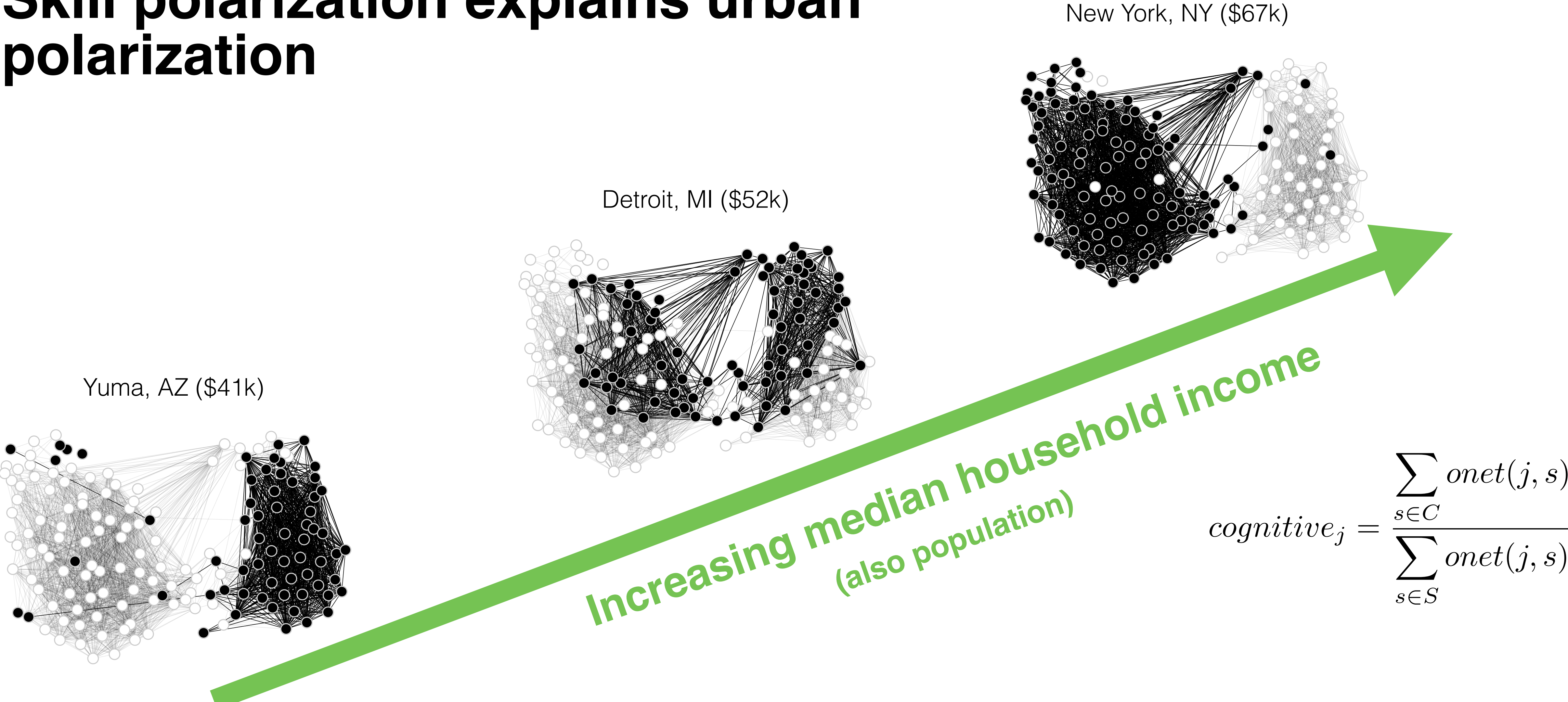
Science Advances (2018)

Skill polarization explains occupational polarization



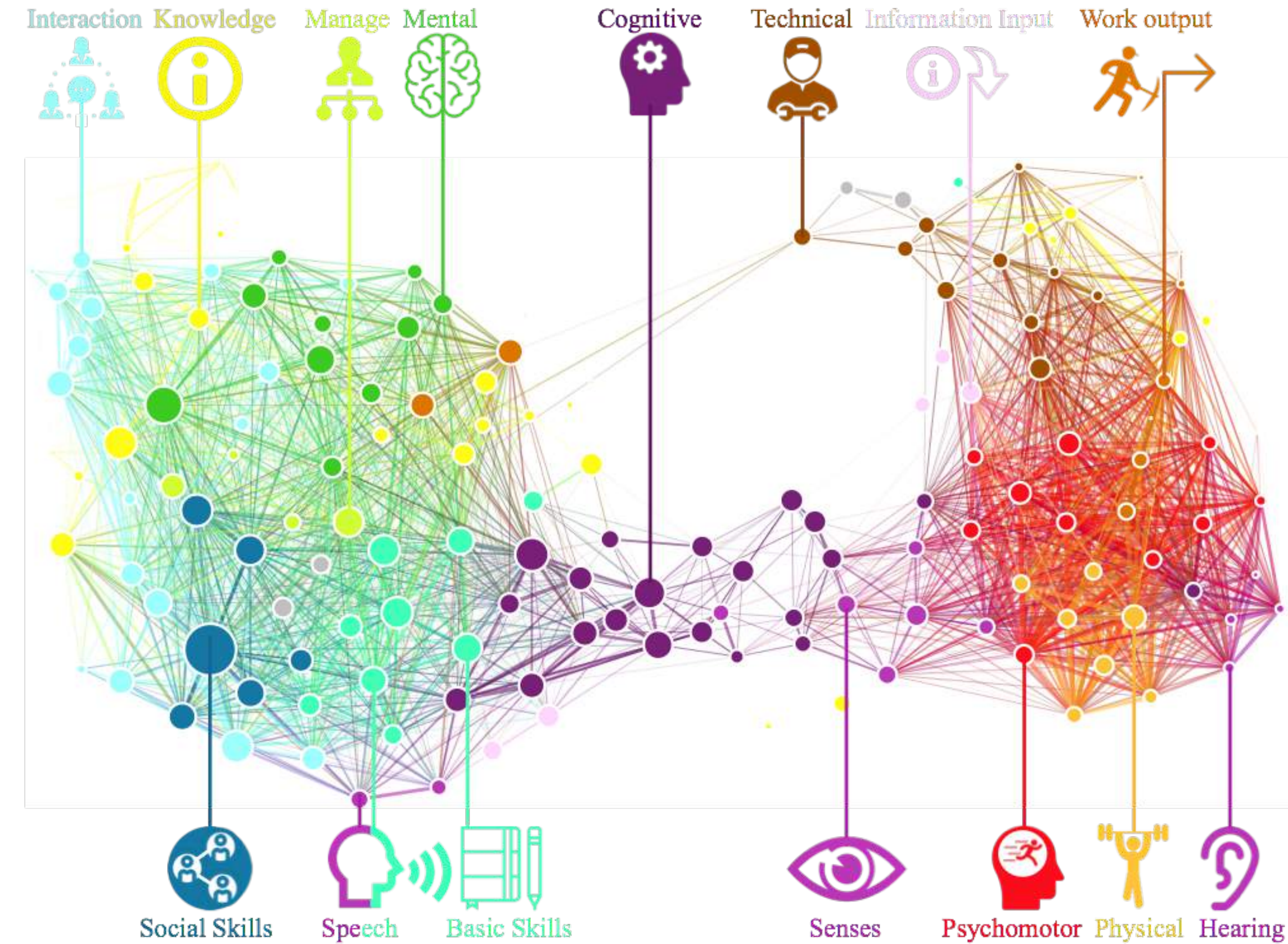
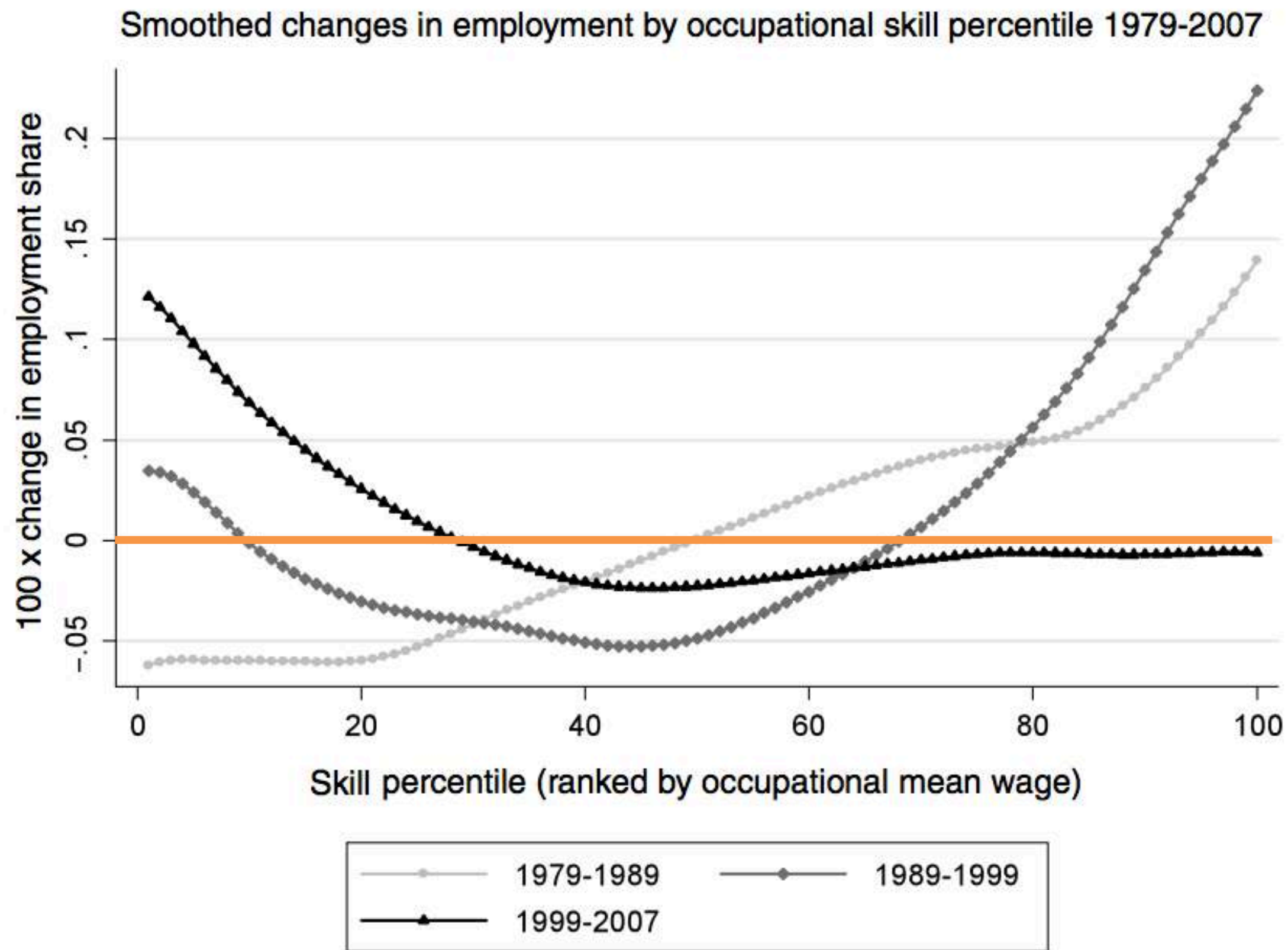
Science Advances (2018)

Skill polarization explains urban polarization



Science Advances (2018)

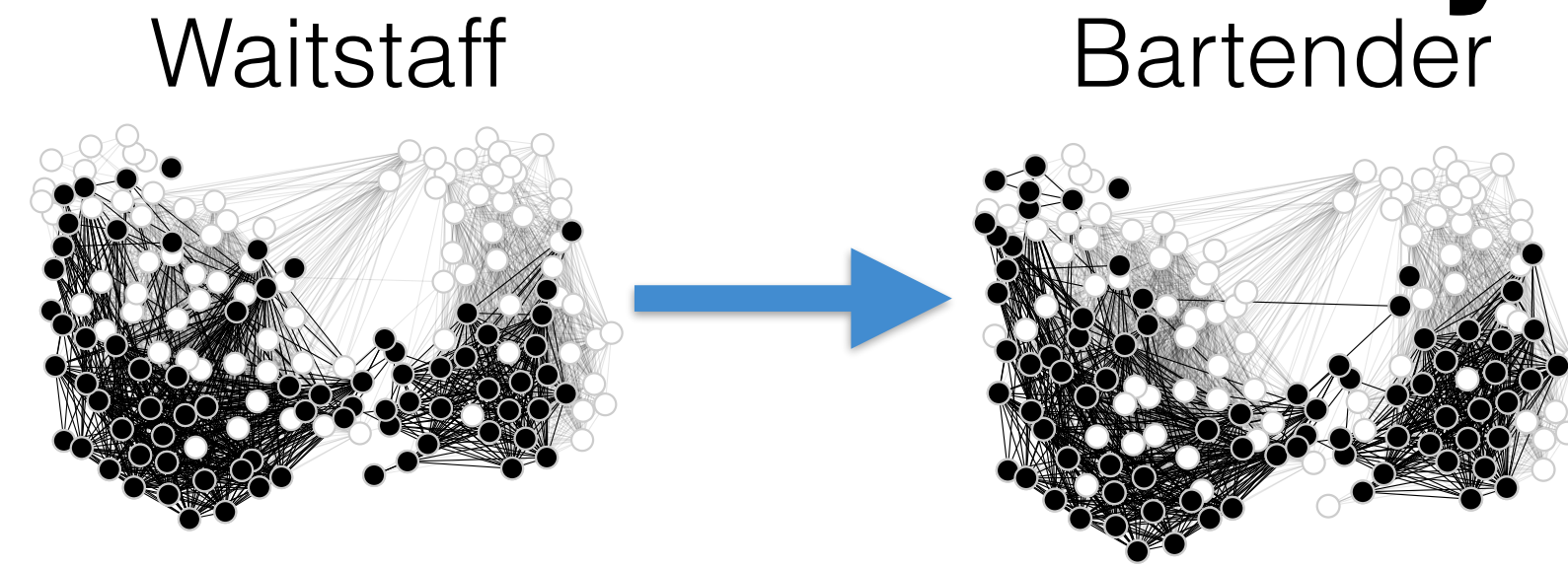
Explaining low- and high-skill employment



The “hollowing of the middle class”

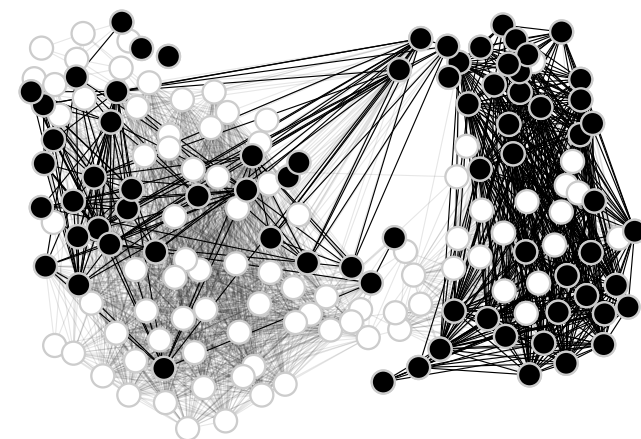
Science Advances (2018)

Skill polarization and career mobility

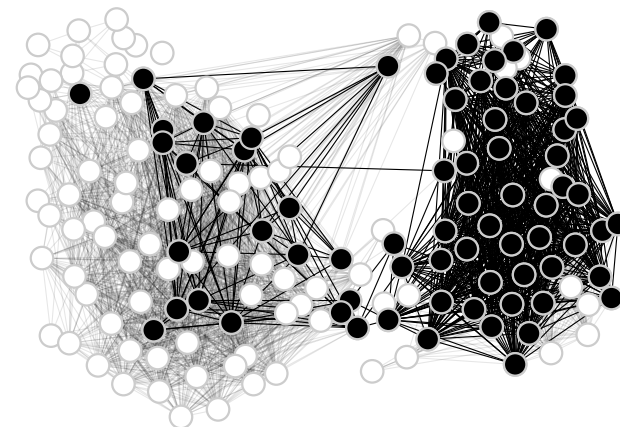


Mid Cognitive Skill

Mechanics Supervisor

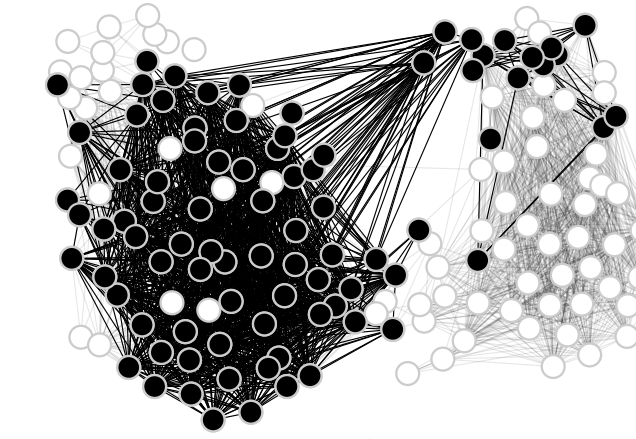


Mechanical Tool Setter

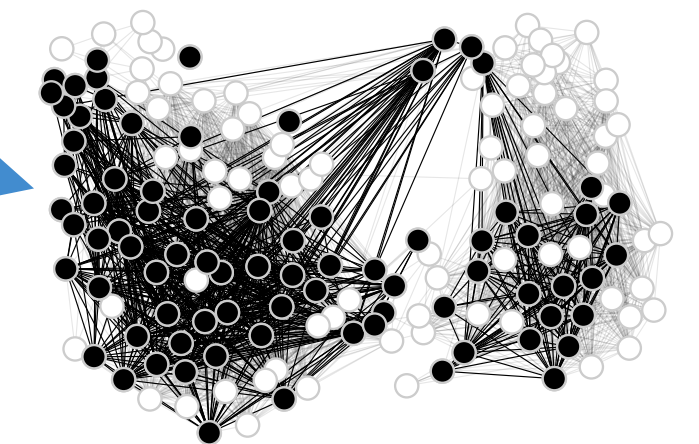


Low Cognitive Skill

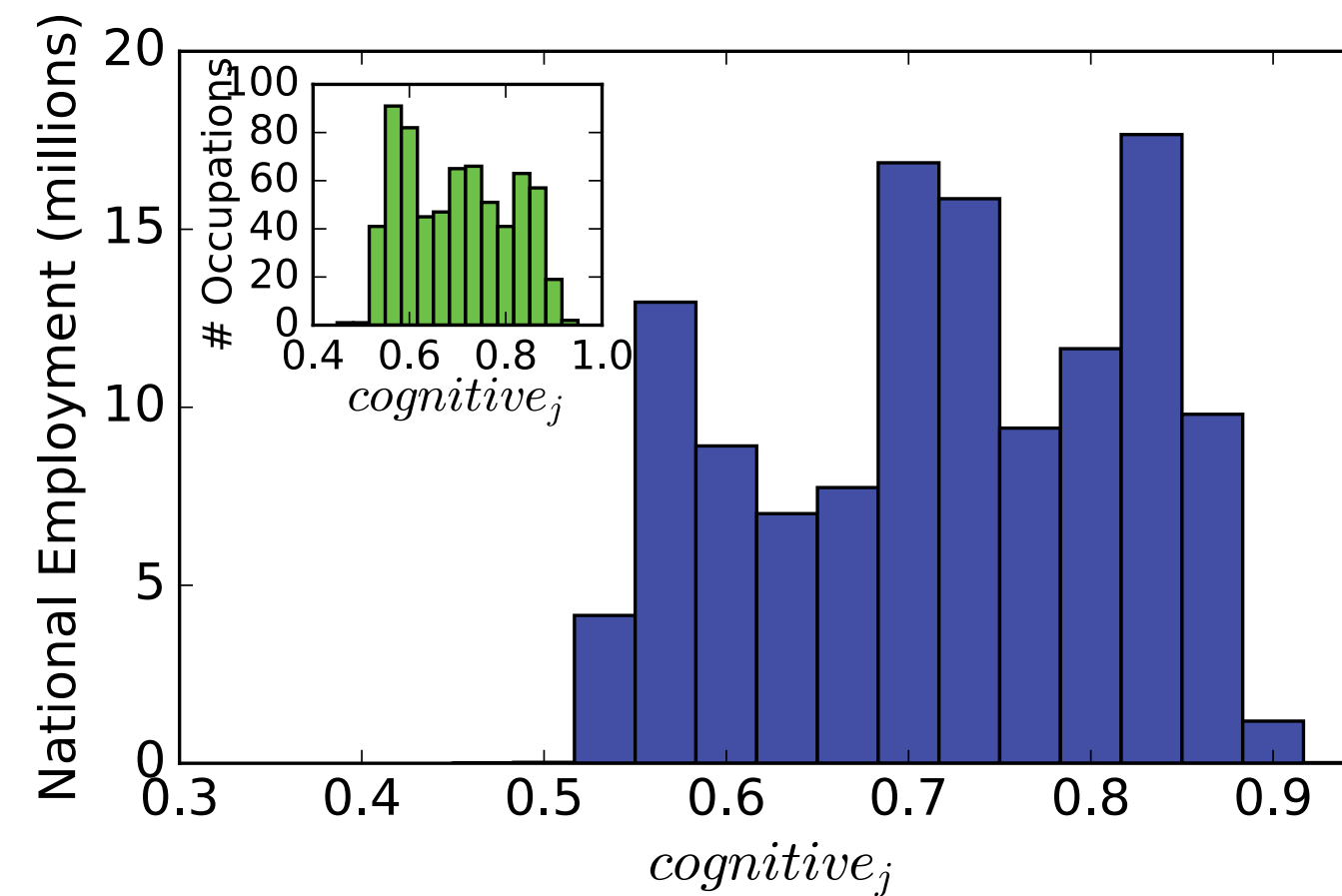
Sales Engineer

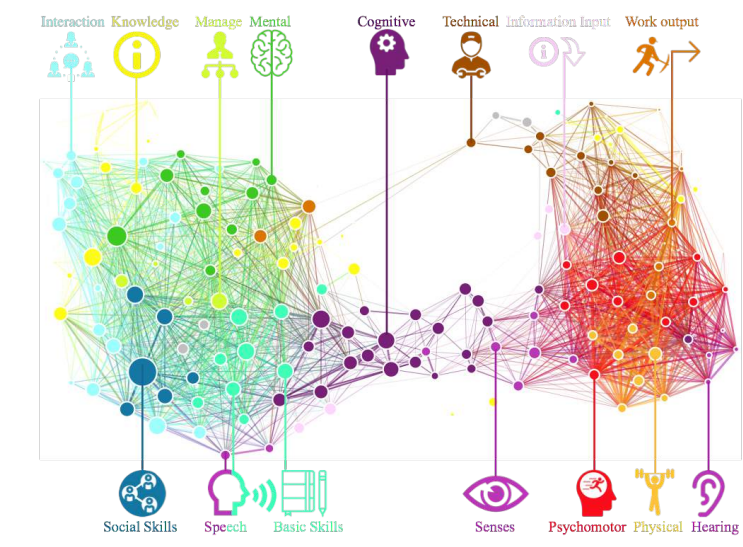


Retail Supervisor

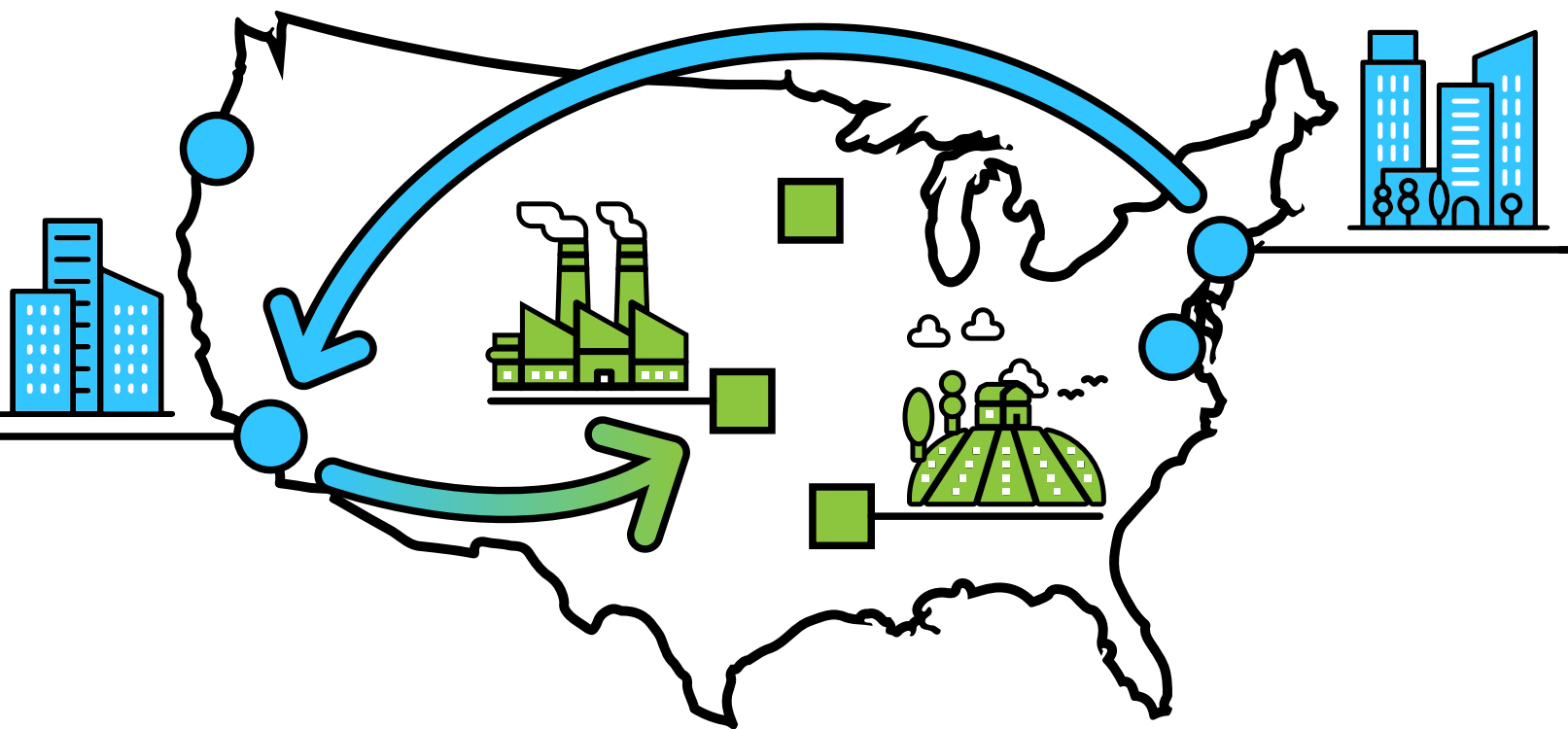


High Cognitive Skill

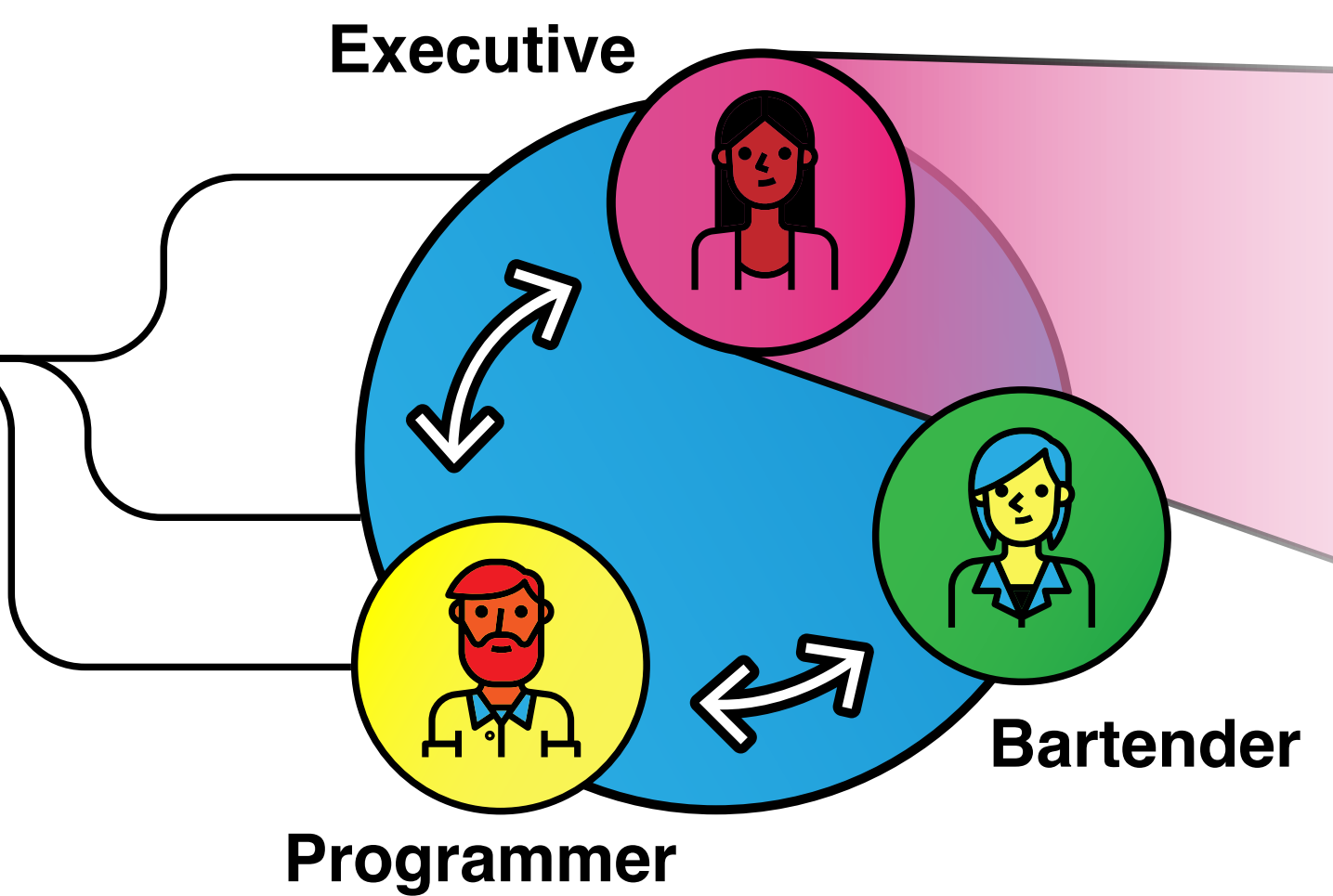




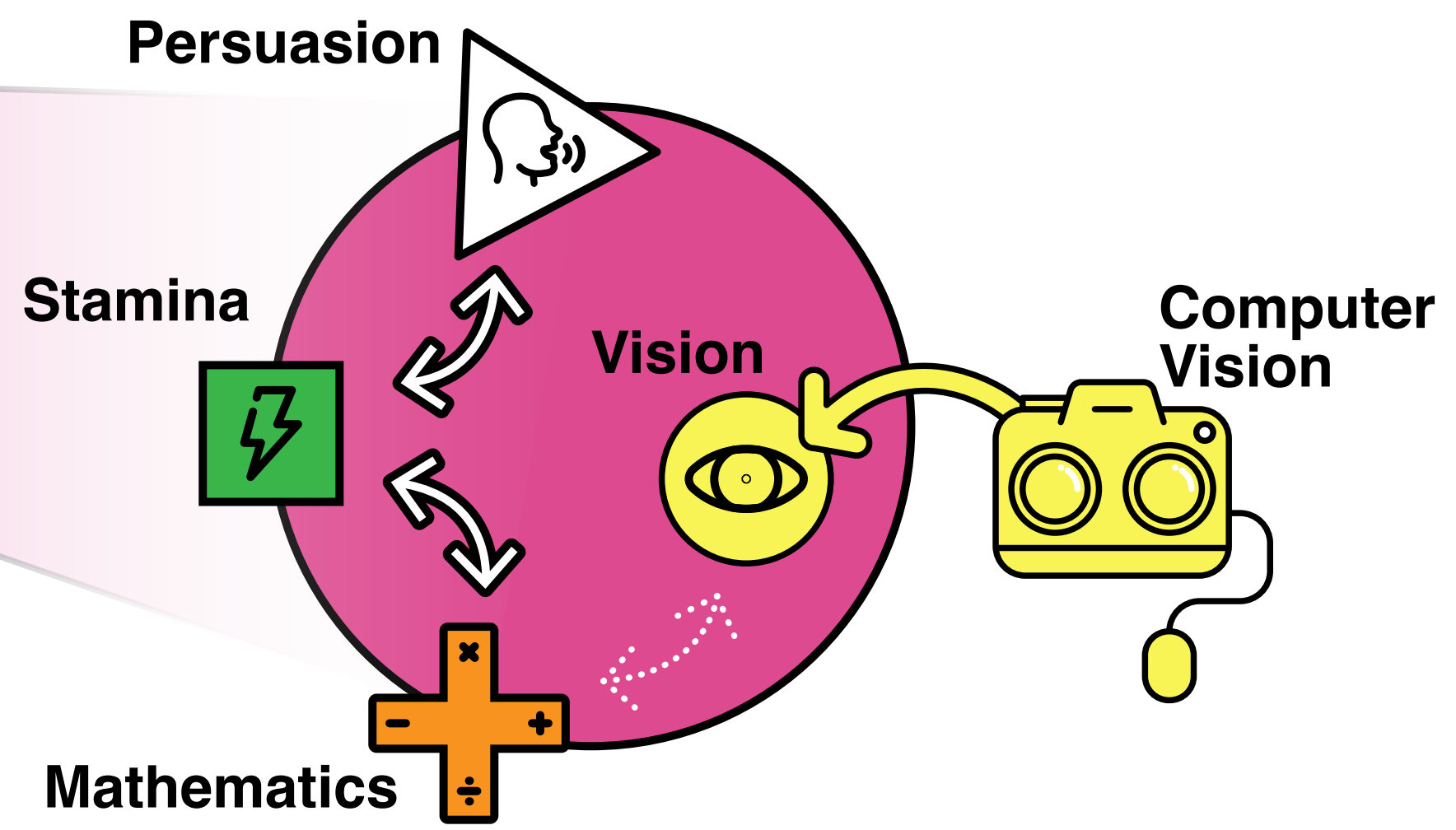
Local Labor Markets



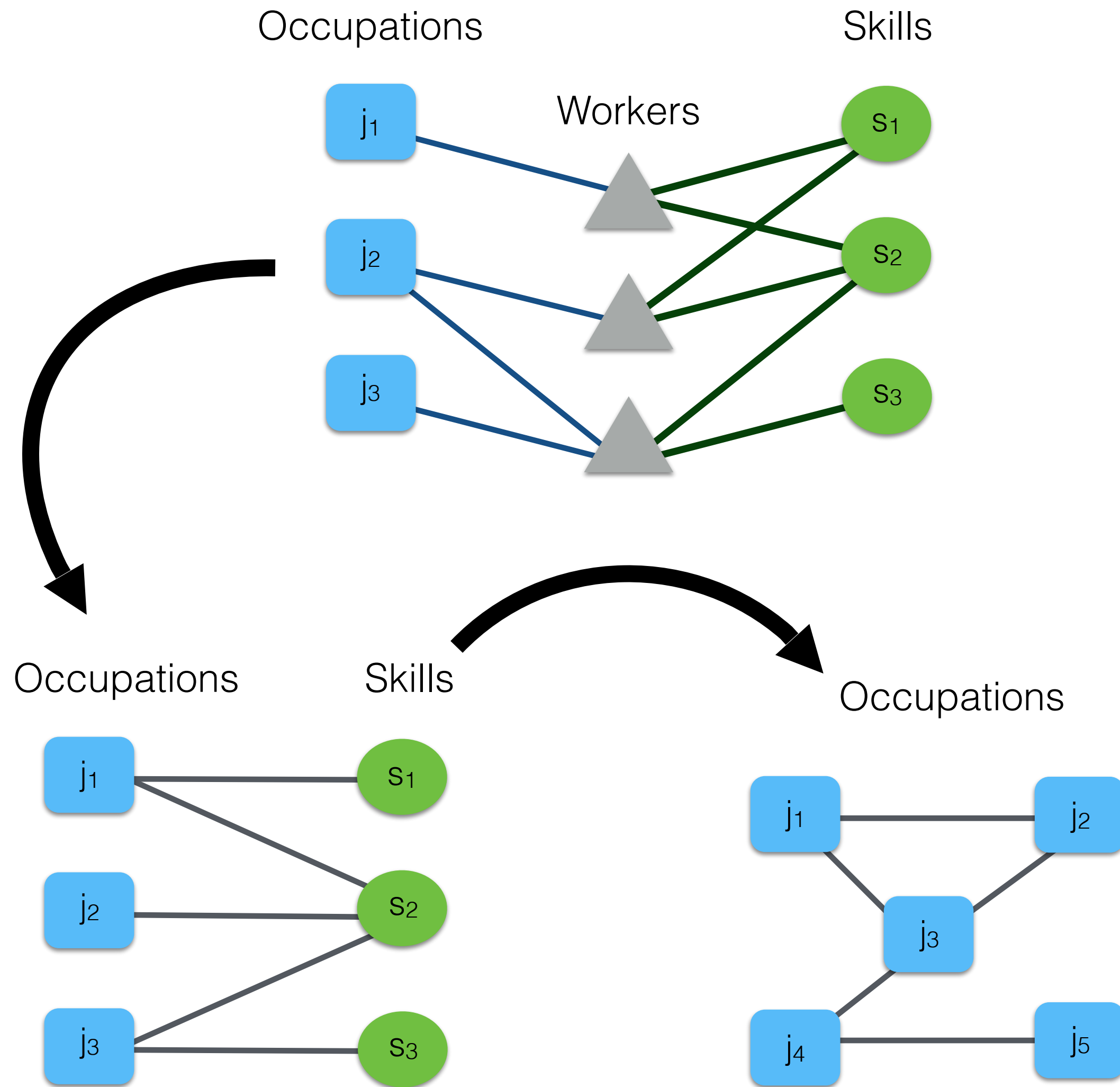
Occupations & Employment



Tasks & Skills



The structure of occupations

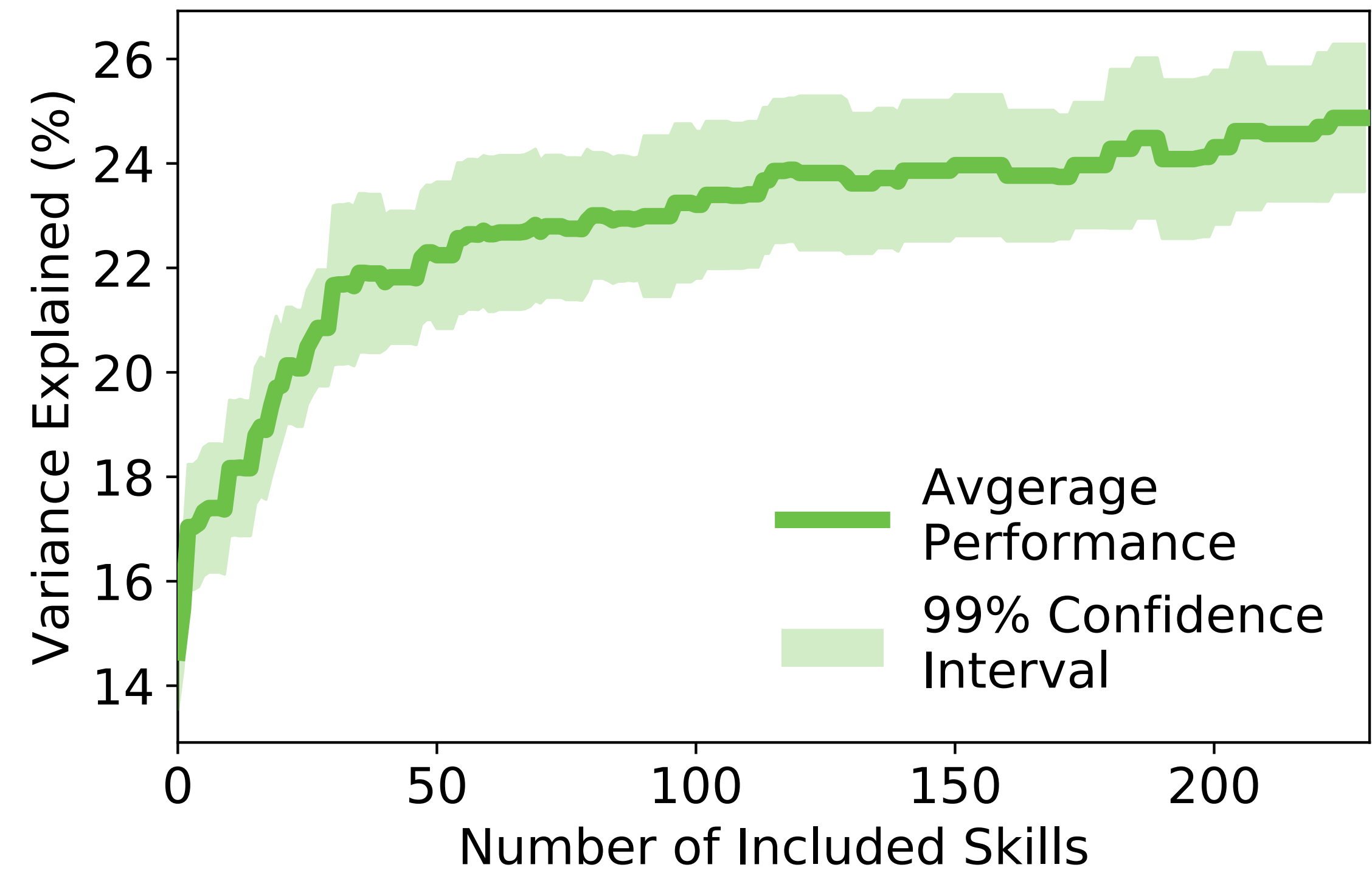


$$rca(j, s) = \frac{onet(j, s) / \sum_{s' \in S} onet(j, s')}{\sum_{j' \in J} onet(j', s) / \sum_{j' \in J, s' \in S} onet(j', s')}$$

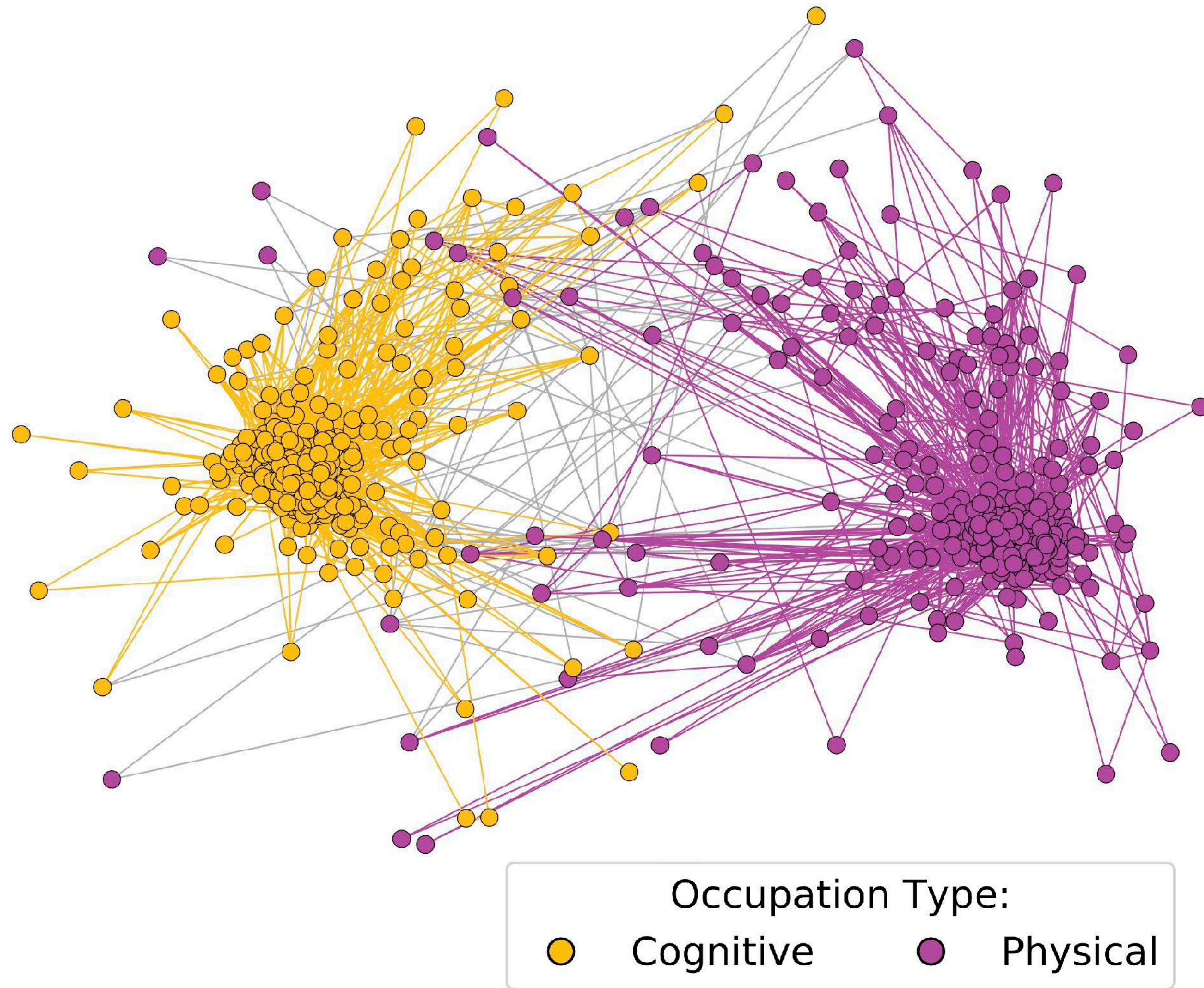
$$I(j, s) = \begin{cases} 1, & \text{if } rca(j, s) > 1 \\ 0, & \text{otherwise} \end{cases}$$

Skill similarity predicts worker mobility

$$skillsim(j, j') = \frac{\sum_{s \in S} I(j, s) \cdot I(j', s)}{\sum_{s \in S} (I(j, s) + I(j', s) - I(j, s) \cdot I(j', s))}$$



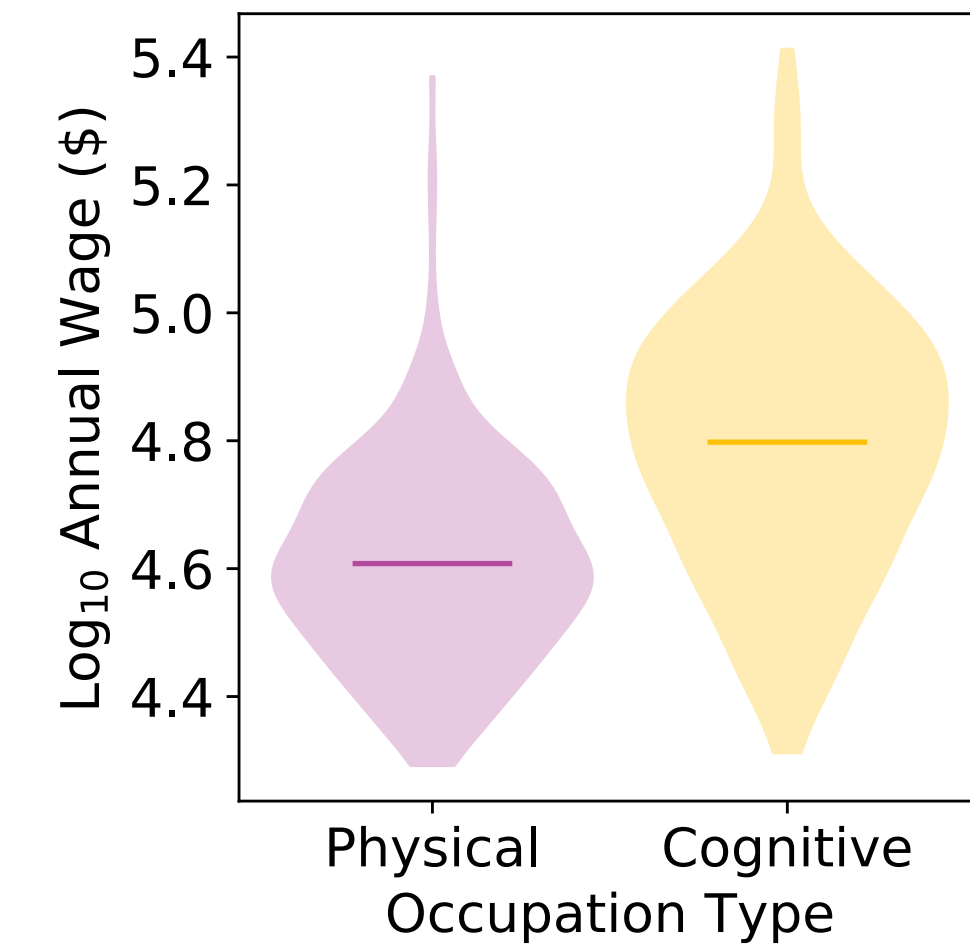
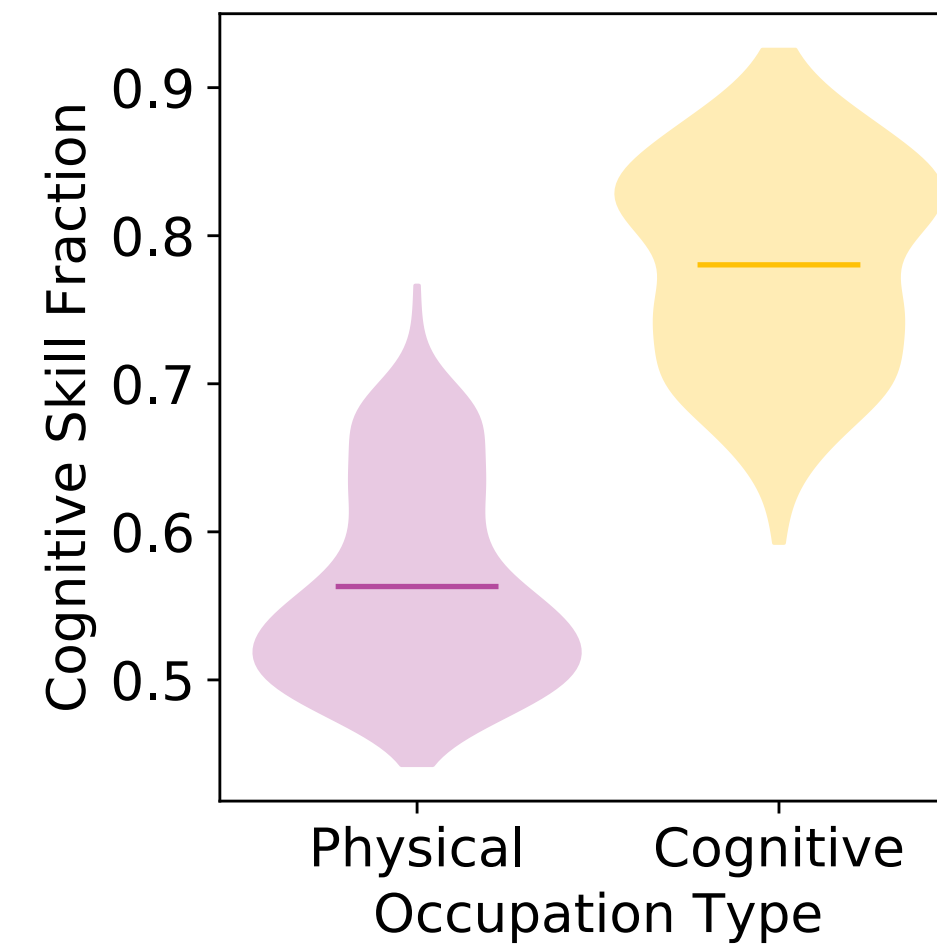
The *polarized* structure of occupations

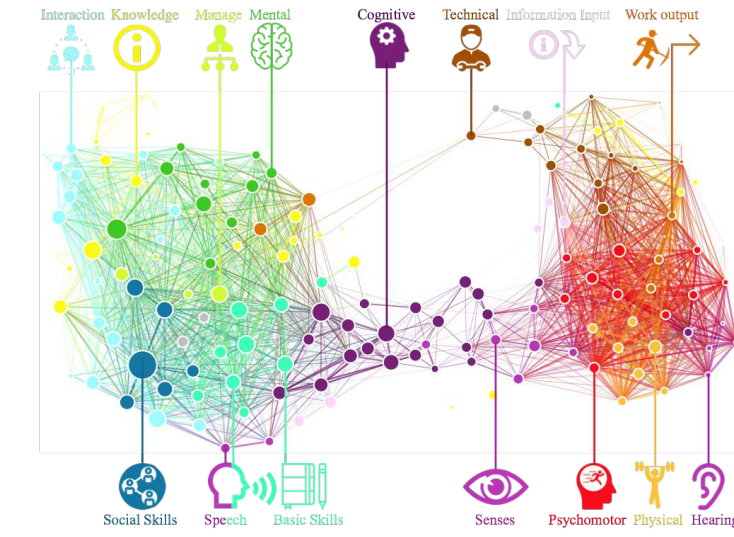
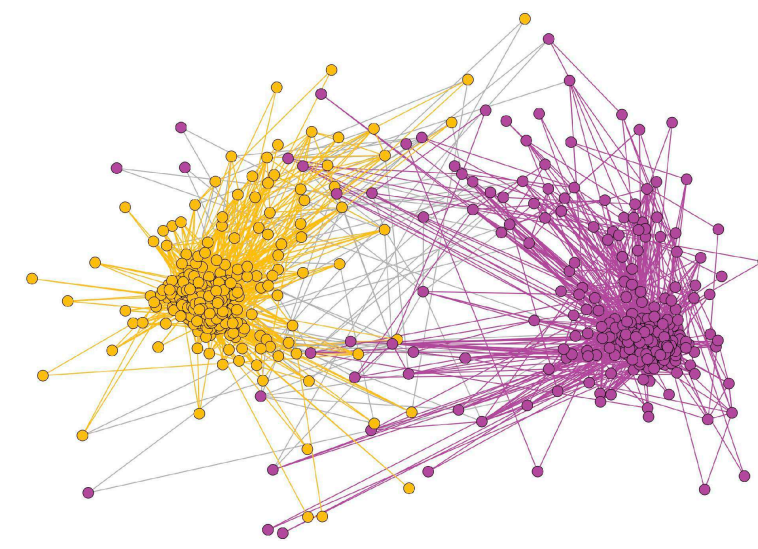


Example Job Titles:

Lawyer
Mathematician
Software Developer
Surgeon
Microbiologist
Chief Executive
Statistician

Bus Driver
Bartender
Dancer
Cook
Carpenter
Car Mechanic
Security Guard
Janitor

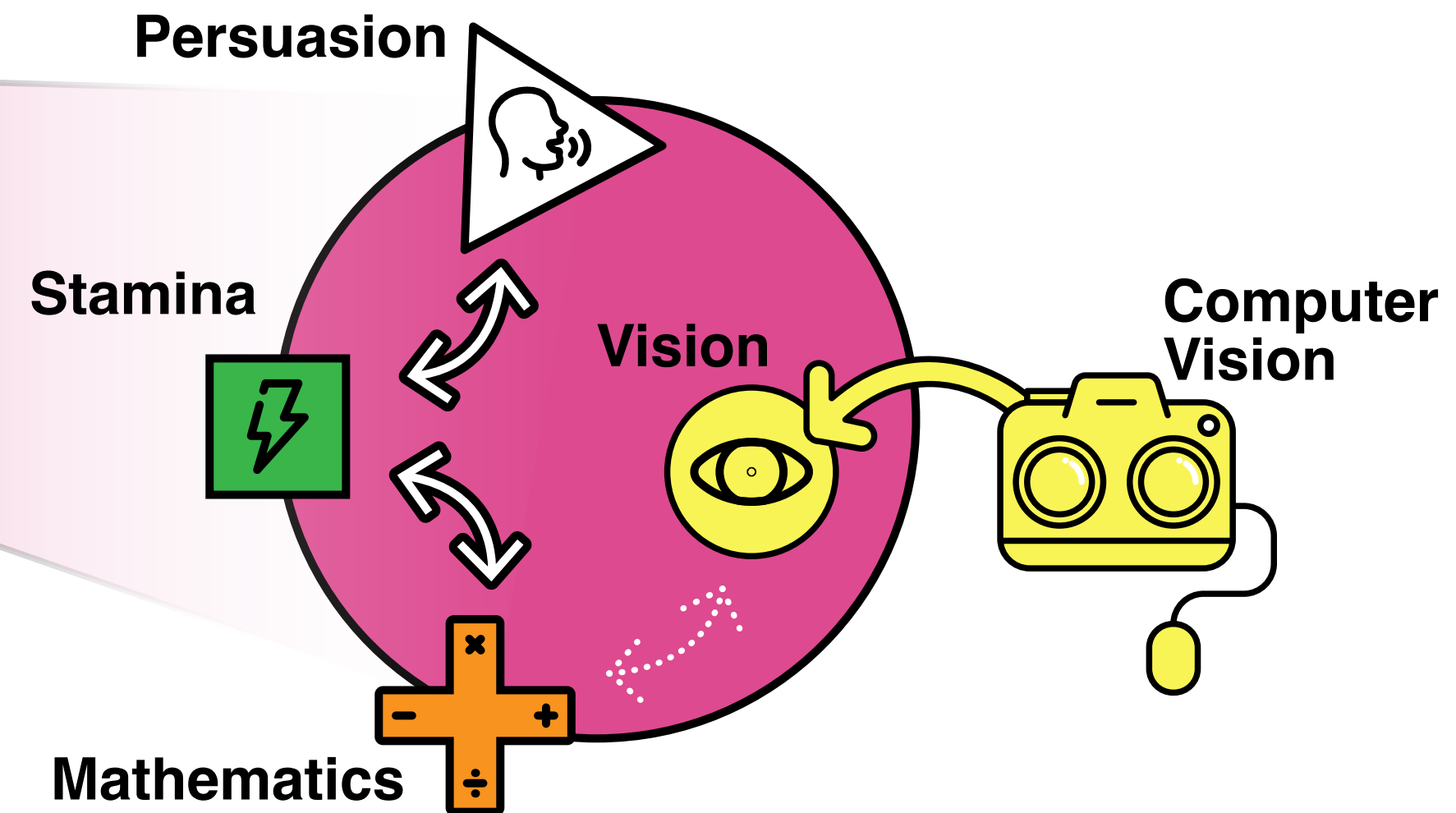
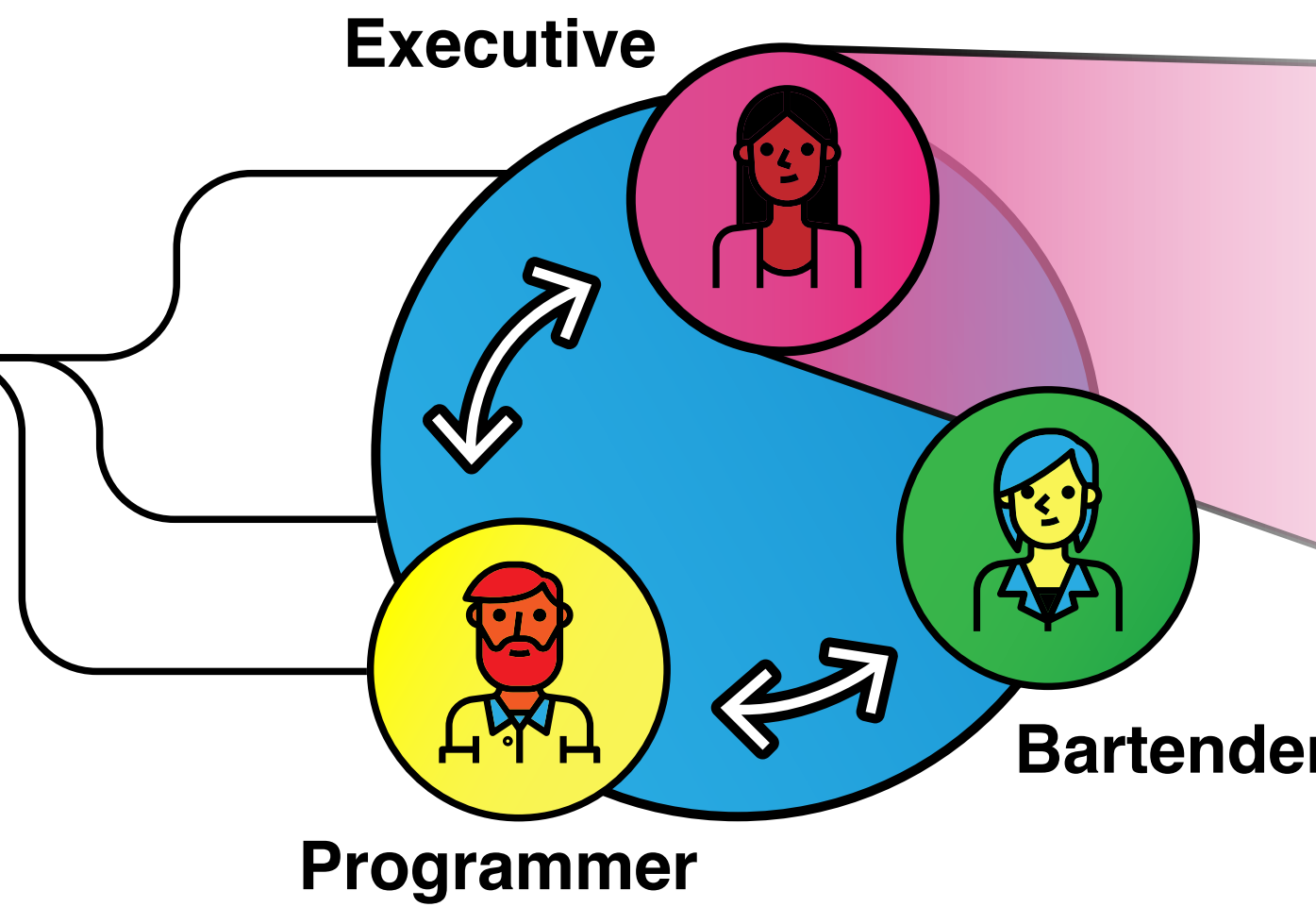
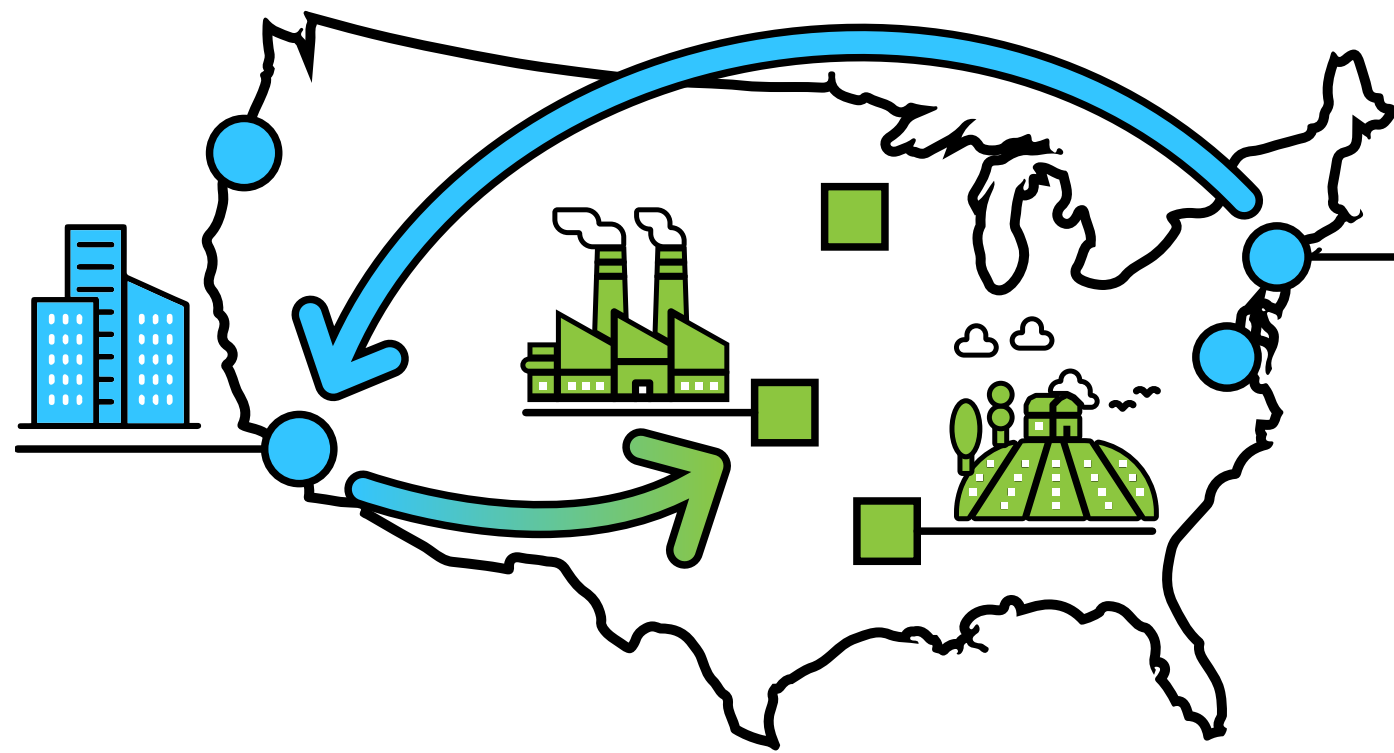




Local Labor Markets

Occupations & Employment

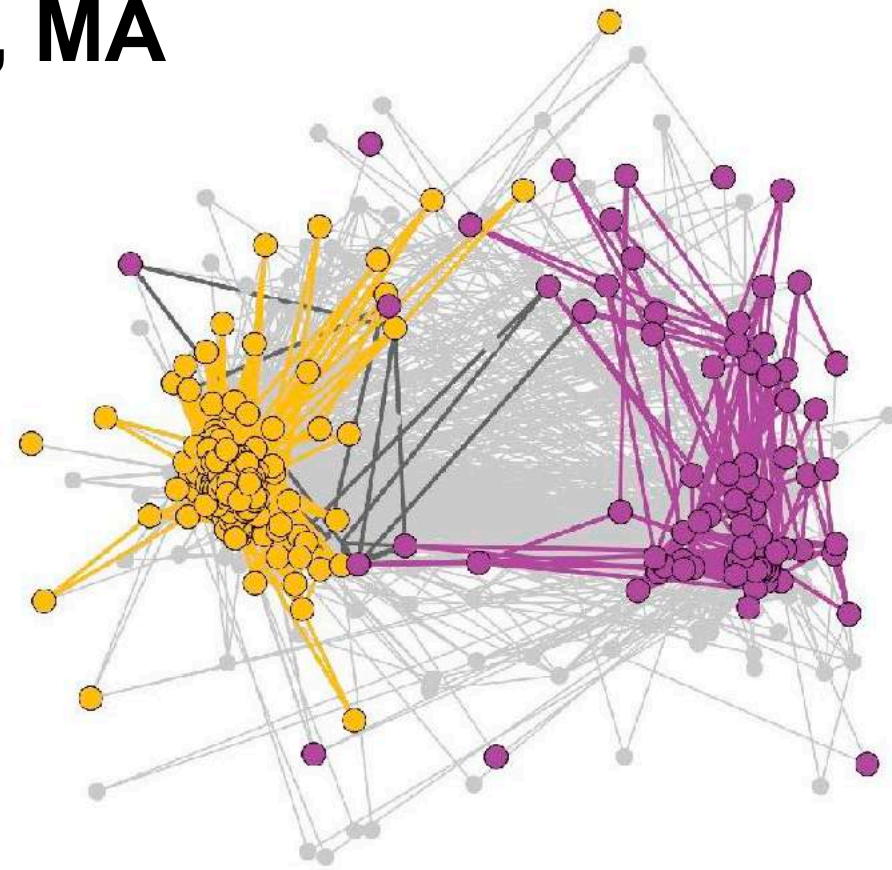
Tasks & Skills



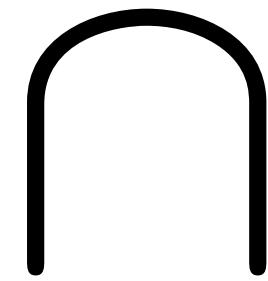
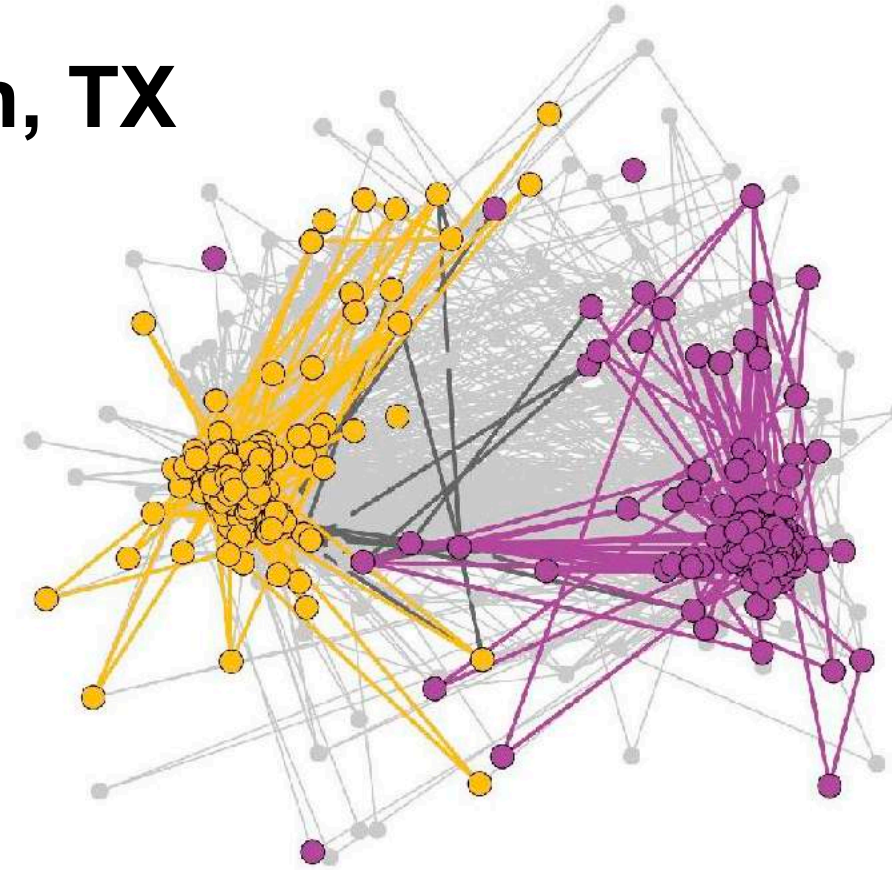
Frank et al., *PNAS* (2019)

Projecting cities onto the job network

Boston, MA
(N=311)

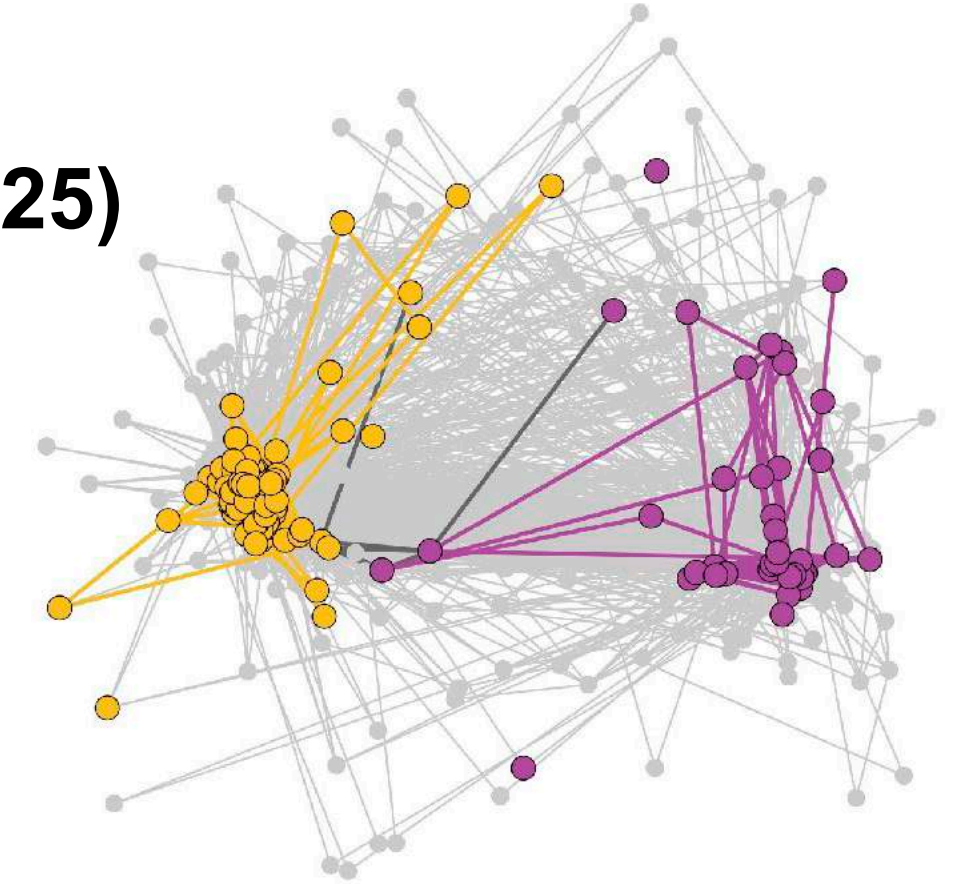


Houston, TX
(N=317)

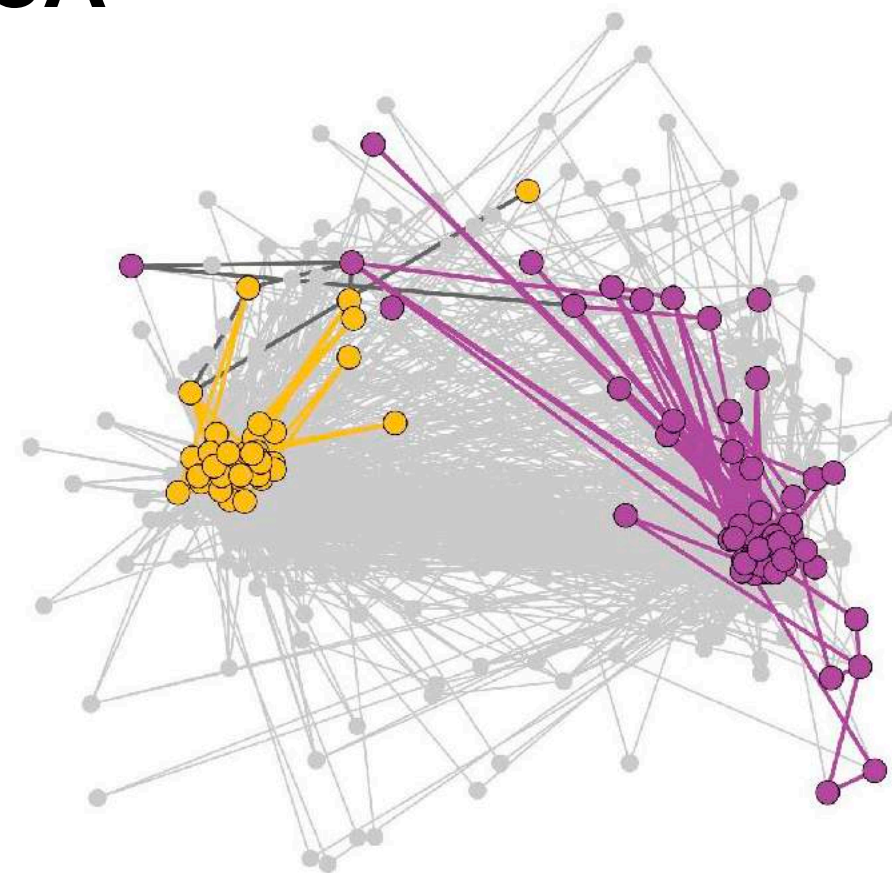


Overlap Network

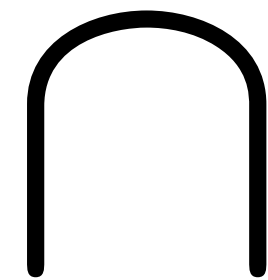
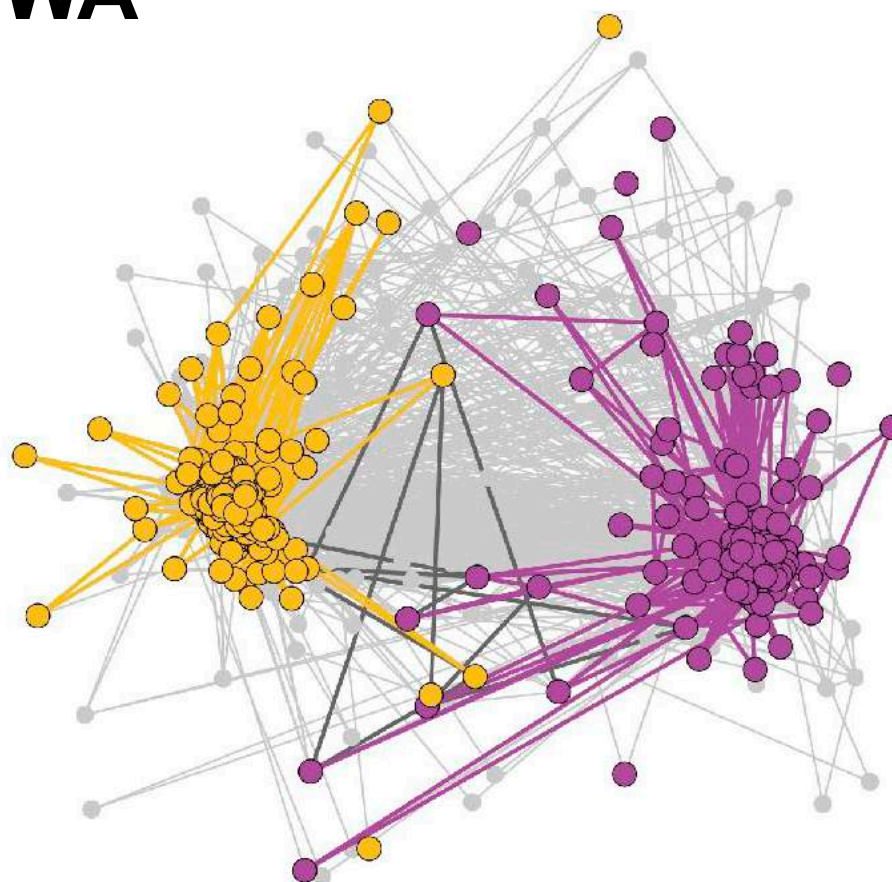
(N=125)



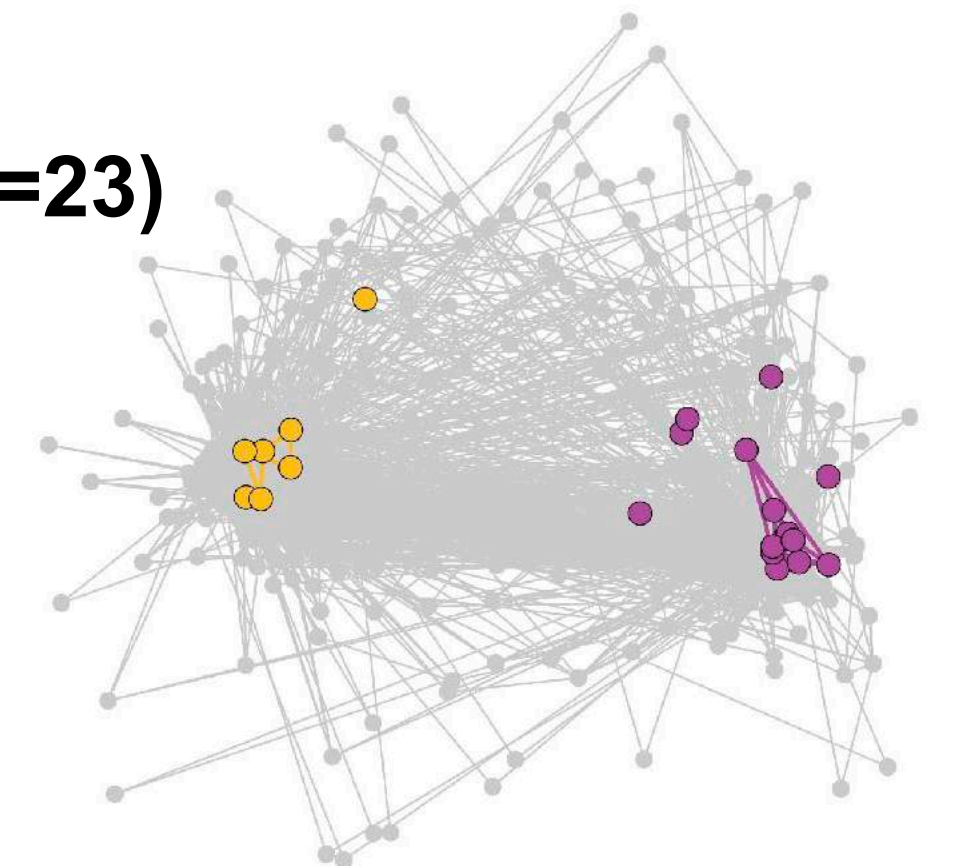
Madera, CA
(N=103)



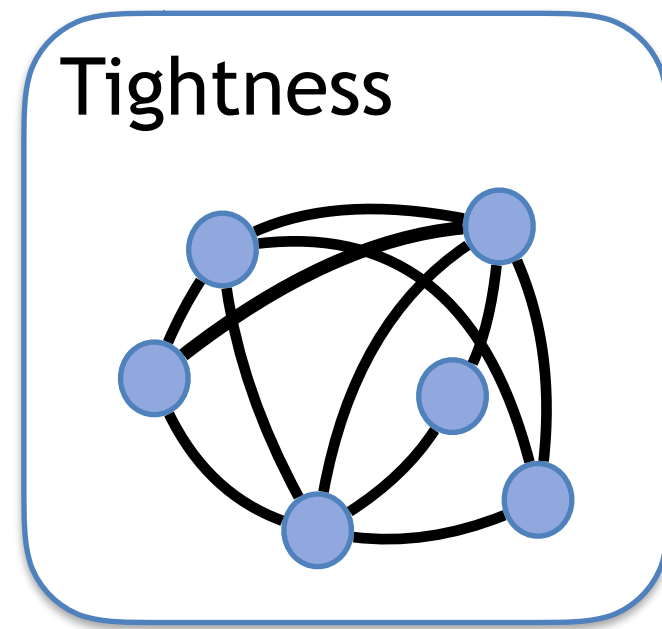
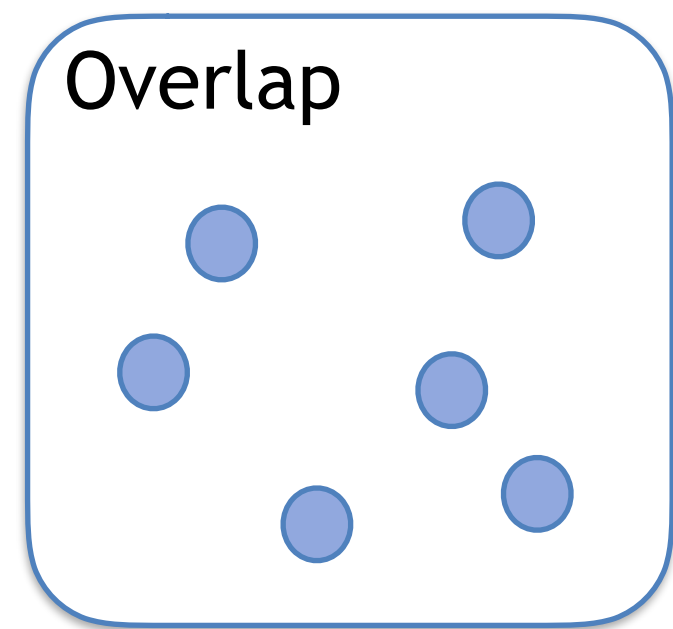
Seattle, WA
(N=330)



(N=23)

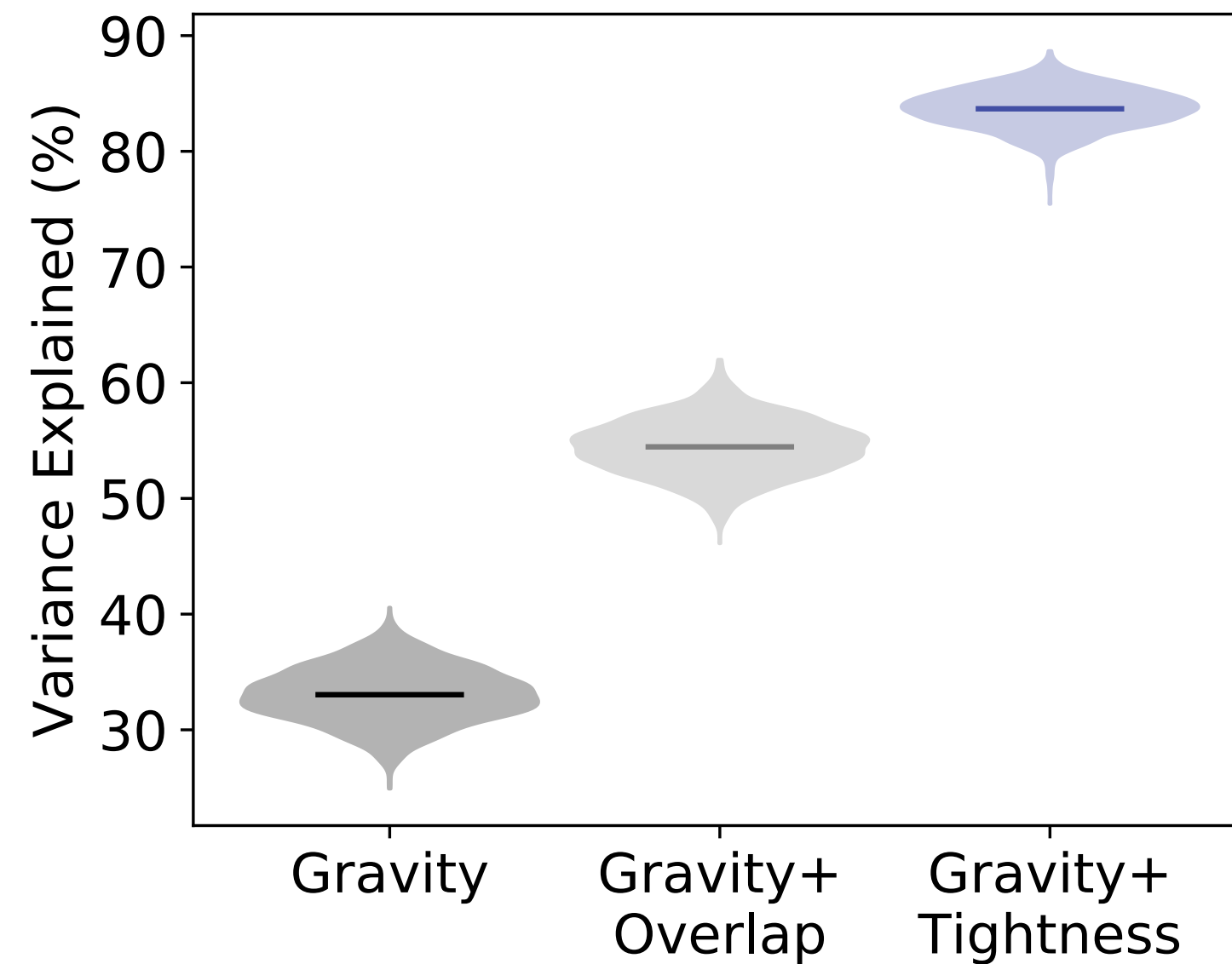


Skills determine spatial mobility

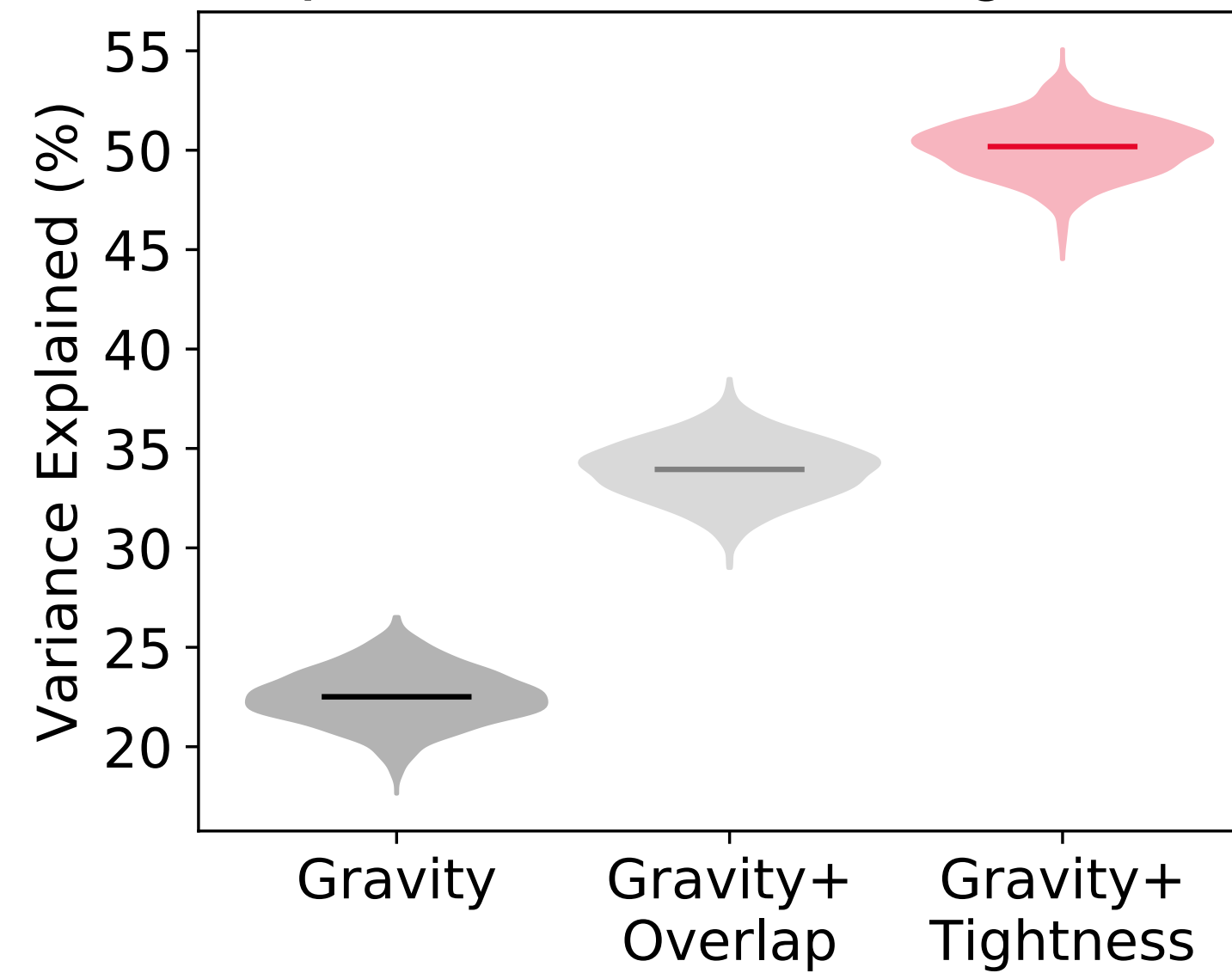


$$tightness(c, c') = \frac{\sum_{j, j' \in J^2} skillsim(j, j') \cdot (I(c, j) + I(c', j))}{2 \cdot \sum_{i, i' \in J^2} skillsim(i, i')}$$

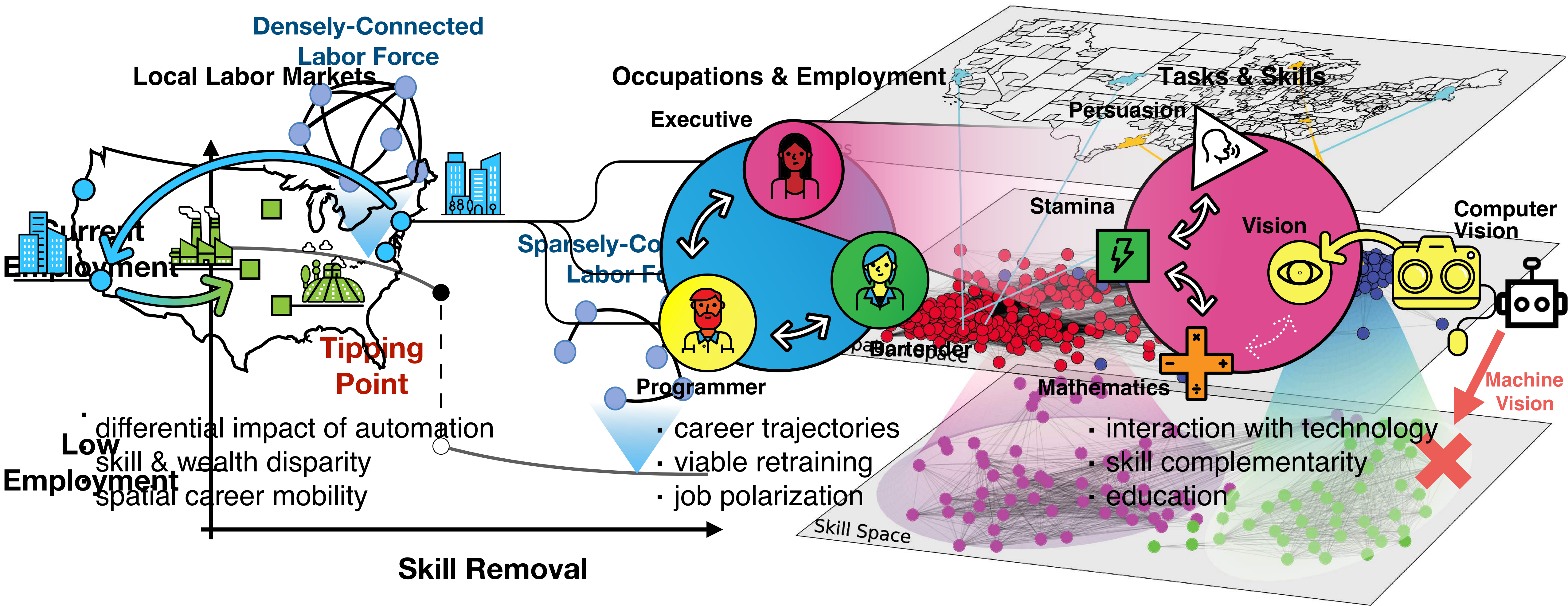
Dependent Variable: Flight Passengers



Dependent Variable: Migration



Structural economic resilience



A
Input

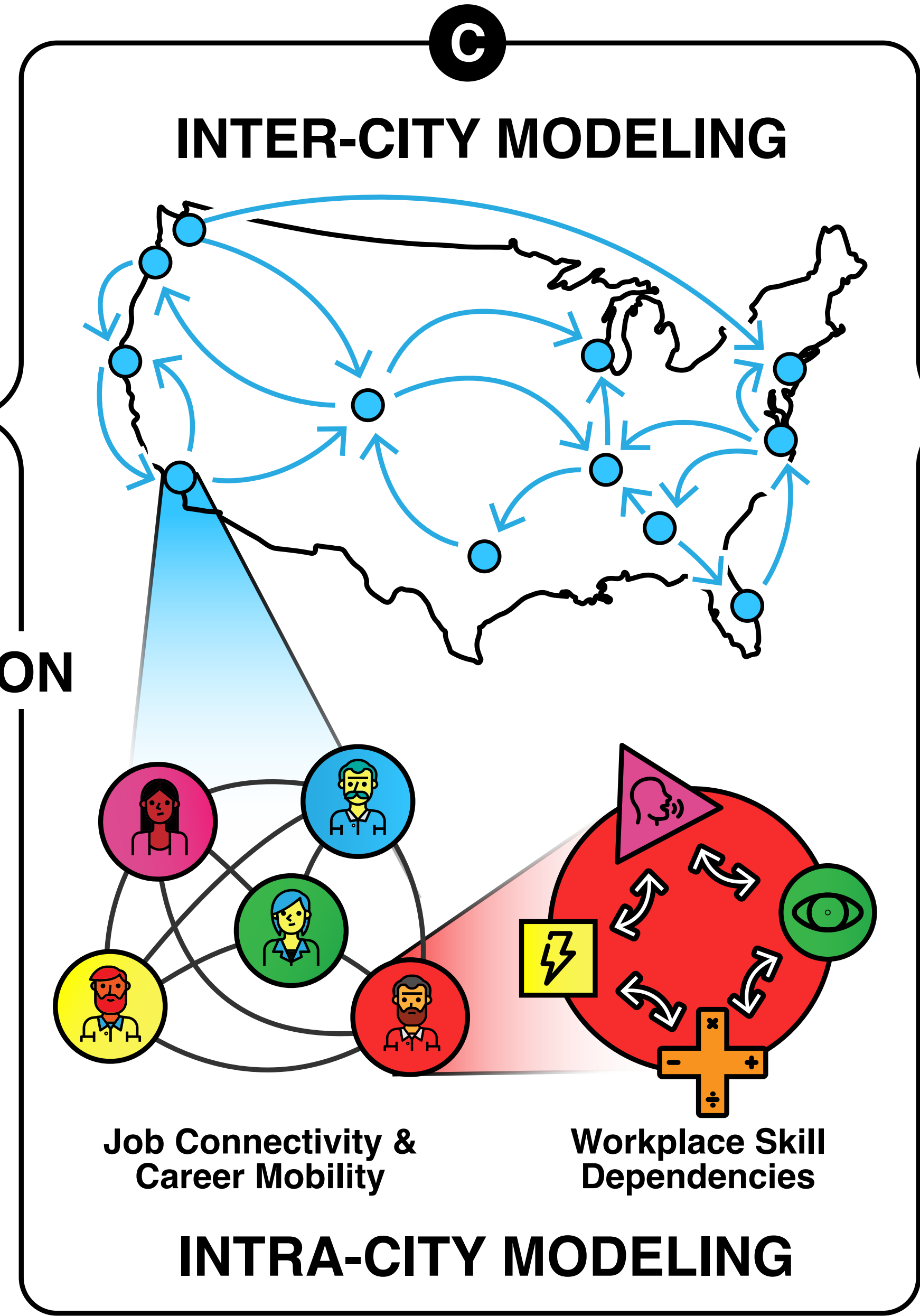
REGIONAL / URBAN LABOR DEPENDENCIES

- employment distribution
- location-specific career data
- longitudinal employment trends

MEASURING SKILL DEMAND

- structured representative survey (e.g. per job title, O*NET)
- microscopic skill perturbations (e.g. patent data)
- unstructured real-time skills data (e.g. per worker or employer, online job postings and resumes)

B
DATA ASSIMILATION



Frank et al., *PNAS* (2019)

- Can retraining programs be more efficient?
- Which workplace activities will be automated?
- What creates economic resilience in cities?
- How can firms maximize returns on investment in technology?

